

A HYPERPARAMETERS OF MCTS

The Monte Carlo Tree Search (MCTS) algorithm [14] used in this study employs hyperparameters in Table 3.

Table 3: MCTS Hyperparameters

Hyperparameter	Description	Default
<i>Main Search Parameters</i>		
c_param	UCT exploration parameter	1.41
max_expansions	Max children per node	3
max_iterations	Max MCTS iterations	20
provide_feedback	Enable feedback	True
best_first	Use best-first strategy	True
value_function_temperature	Value function temperature	0.2
max_depth	Max tree depth	20
<i>UCT Score Calculation Parameters</i>		
exploration_weight	UCT exploration weight	1.0
depth_weight	Depth penalty weight	0.8
depth_bonus_factor	Depth bonus factor	200
high_value_threshold	High-value node threshold	55
low_value_threshold	Low-value node threshold	50
very_high_value_threshold	Very high-value threshold	75
high_value_leaf_bonus_constant	High-value leaf bonus	20
high_value_bad_children_bonus_constant	High-value bad children bonus	20
high_value_child_penalty_constant	High-value child penalty	5
<i>Action Model Parameters</i>		
action_model_temperature	Action model temperature	0.7
<i>Discriminator Parameters</i>		
number_of_agents	Number of Discriminator Agents	5
number_of_round	Number of debate rounds	3
discriminator_temperature	Discriminator temperature	1

B COMPARISON WITH VANILLA RAG

In Table 5, we compare two RAG-based approaches: 1. Direct Issue Patch: We use issue-patch pairs from retrieved instances with similar error types as demonstrations for in-context learning (ICL) without experiences extraction; 2. RAG w/o LLM-Reranking: We use the most similar retrieved experiences without LLM reranking for issue resolution.

Table 4: Comparison with vanilla RAG.

Method	Pass@1	Δ
SWE-Exp	41.0%	-
w/o Experiences Extraction	36.0%	-5.0%
w/o LLM Reranking	38.2%	-2.8%

C HEAD-TO-HEAD COMPARISON

For memory-enhanced agent, we adapted EvoCoder, a experience-enhanced agent that leverages both intra-repository and cross-repository experience to reproduce errors, for the issue resolution task, achieving 38.0% Pass@1 on SWE-bench-Verified.

For multi-agent method, we also reproduced another multi-agent approach, CodePlan, where a PlanAgent decomposes the problem statement into sequential sub-goals solved by specialized agents via moatless-tools. In contrast, our method achieves substantially better performance, while CodePlan only reached 35.2% Pass@1.

For graph-guided agent, we also evaluated LocAgent [4], a multi-agent approach that leverages code graph structures and tool-driven search. It achieved 37.4% Pass@1, still lower than our method.

To assess compatibility, we integrated Skywork-SWE-32B into our framework and evaluated it on a subset of 75 instances (25 each from Django, SymPy, and Sphinx), achieving a Pass@1 of 37/75 compared to 29/75 without our method, as summarized in Table 6. This empirical evidence indicates that our framework operates orthogonally to training-enhanced repair models, enabling seamless integration.

Table 5: Head-to-Head Comparison with representative related studies.

Method	Pass@1
SWE-Exp	42.6%
EvoCoder	38.0%
CodePlan	35.2%
LocAgent + SWE-Search	37.4%

Table 6: Experimental results of Skywork-SWE-32B.

Model	Pass@1	Δ
Skywork-SWE-32B	38.67%	-
w/ SWE-Exp	49.33%	+10.66%

D VARIANTS

Table 7 reports the results of our method with and without the testbed, while Table 8 compares results when experiences from the target repository are either included or excluded. Experimental results show that our method can further surpass the current method of the same model by equipping with the testbed or internal experiences.

Table 7: Experimental results w/ and w/o testbed.

Variants	Pass@1
SWE-Exp w/ testbed	42.0%
SWE-Exp w/o testbed	41.0%
SWE-Search w/ testbed	37.0%
SWE-Search w/o testbed	35.4%

Table 8: Experimental results w/ and w/o internal experiences.

Variants	Pass@1
SWE-Exp w/ internal	42.6%
SWE-Exp w/o internal	41.0%

E RESULTS ON DIFFERENT MODELS

As shown in Table 6, we evaluate GPT-4o with SWE-Exp on SWE-Bench-Verified. Notably, our approach continues to perform robustly on the GPT-4o model, outperforming state-of-the-art method for the same model (AutoCodeRover, 38.4%), which highlights the generalizability and effectiveness of our method.

Table 9: Experimental results with different models.

Method	Model	Pass@1
Agentless	👤 DeepSeek-V3-0324	36.6%
	🔒 GPT-4o (2024-05-13)	36.2%
SWE-Agent	👤 DeepSeek-V3-0324	38.8%
	🔒 Claude-3.5 Sonnet	33.6%
SWESynInfer	🔒 GPT-4o (2024-05-13)	23.0%
	🔒 Claude-3.5 Sonnet	35.4%
	🔒 GPT-4o (2024-05-13)	31.8%
	👤 Lingma SWE-GPT 72B	32.0%
SWE-Search	👤 DeepSeek-V3-0324	35.4%
Moatless Tools	👤 DeepSeek-V3-0324	34.6%
AutoCodeRover	🔒 GPT-4o (2024-05-13)	38.4%
CodeAct	🔒 GPT-4o (2024-05-13)	30.0%
OpenHands	👤 DeepSeek-V3-0324	38.8%
EvoCoder	👤 DeepSeek-V3-0324	38.0%
CodePlan	👤 DeepSeek-V3-0324	35.2%
LocAgent + SWE-Search	👤 DeepSeek-V3-0324	37.4%
SWE-Exp	👤 DeepSeek-V3-0324	41.0%
	🔒 GPT-4o (2024-05-13)	40.6%

F COST ANALYSIS AND TOOLSETS

Table 10 presents the cost comparison of DeepSeek-V3-0324 between SWE-Exp (SWE-Exp) and SWE-Search. While SWE-Exp employs a more sophisticated dual-agent architecture together with retrieval, the additional overhead is modest. Specifically, the average token usage only slightly increases (203.3K vs. 189.1K), and the average USE cost remains nearly unchanged (\$0.13 vs. \$0.12). Although retrieval adds 37s to the pipeline, the total wall time is only marginally longer (15min 49s vs. 12min 37s). These results highlight that the performance improvements of SWE-Exp are achieved with minimal additional computational and monetary costs.

Table 10: Efficiency Metrics.

Metrics	SWE-Exp	SWE-Search
Average Token Costs	203.3K	189.1K
Average USD Costs	\$0.13	\$0.12
Average Wall Time	15min49s	12min37s
Average Retrieval and rerank time	37.5s	-

G IMPACT OF EXPERIENCE BANK SIZE

We conducted experiments on a subset with 75 instances (25 from Django, 25 from SymPy, and 25 from Sphinx). As shown in Figure 6, we analyzed the effect of experience-bank growth by adding experiences in increments of 100. We observed that Pass@1 steadily increases until around 300 experiences. Beyond 300 experiences, Pass@1 enters a plateau, exhibiting only minor fluctuations of 1–2 points. All experience additions follow the chronological order, simulating realistic accumulation of experience over time.

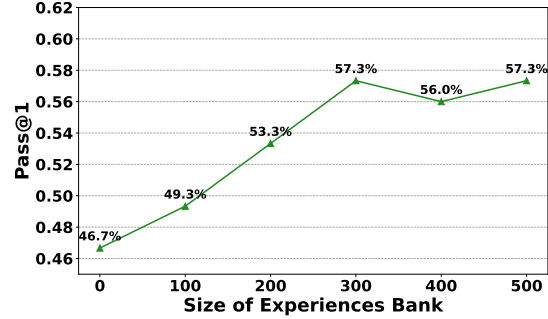


Figure 6: Impact of the number of experiences.

H PROMPT TEMPLATES

In the following section, we provide a comprehensive enumeration of all prompts employed throughout our workflow, including the system prompts used by the dual-agent architecture, the prompts designed for extracting successful and failed experiences, and those used for reusing past experiences. This detailed documentation aims to ensure reproducibility and to highlight the role of prompt engineering in the effectiveness of our method.

H.1 Instructor

Prompt 1: Instructor Prompt

You are an autonomous AI instructor with deep analytical capabilities. Operating independently, you cannot communicate with the user but must analyze the past history of interactions with the code repository to generate the next instruction that guides the assistant toward completing the task.

Workflow to guide assistants in modifying code

Follow these structured steps to understand the task and instruct the assistant to locate context, and perform code modifications.

1. Understand the Task

- Carefully read the <task> to determine exactly what is known and what still needs to be clarified according to the interaction history.
- Focus on the cause of the <task> and suggested changes to the <task> that have been explicitly stated in the <task>.

```

1625     - Compare <task> with the code from the
1626       interaction history, determine what
1627       additional context (files, functions,
1628       dependencies) may be required. Request
1629       more information if needed.
1630
1631   ### 2. Locate Code
1632   - Using your analysis, generate instructions
1633     to guide assistant to locate the exact
1634     code regions to understand or modify.
1635   - Once the location of the code that needs to
1636     be modified is determined, instruct
1637     assistant to modify it and provide the
1638     exact location.
1639   - Narrow down the scope of the code you need
1640     to look at step by step.
1641
1642   ### 3. Modify Code
1643   - The generated instruction should only focus
1644     on the changes needed to satisfy the task
1645     . Do not modify unrelated code.
1646   - The instructions for modifying the code need
1647     to refer to the task and the relevant
1648     code retrieved, rather than being based
1649     on your own guesses.
1650   - Keep the edits minimal, correct, and
1651     localized.
1652   - If the change involves multiple locations,
1653     apply atomic modifications sequentially.
1654
1655   ### 4. Iterate as Needed
1656   - If the task has already been resolved by the
1657     existing code modifications, finish the
1658     process without making additional changes
1659     .
1660   - If the task is not fully resolved, analyze
1661     what remains and focus only on the
1662     unresolved parts.
1663   - Avoid making unnecessary changes to
1664     previously correct code modifications.
1665     Subsequent edits should strictly target
1666     the remaining issues.
1667   - When modifying the input parameters or
1668     return values of a function or class,
1669     make sure to update all relevant code
1670     snippets that invoke them accordingly.
1671   - But do not take test into account, just
1672     focus on how to resolve the task.
1673   - Repeat until the task are resolved.
1674
1675   ### 5. Complete Task
1676   - Once the implementation satisfies all task
1677     constraints and maintains system
1678     integrity:
1679     - Do not add additional test cases.
1680     - Stop the task.
1681
1682   # Additional Notes
1683
1684   * **Think Step by Step**
1685   - Always document your reasoning and thought
1686     process in the Thought section.
1687   - Only one kind of instruction is generated
1688     each step.
1689
1690   * **Efficient Operation**

```

```

1683     - Use previous observations to inform your next
1684       actions.
1685   - Avoid instructing assistant to execute
1686     similar actions as before.
1687   - Focus on minimal viable steps: Prioritize
1688     actions that maximize progress with
1689     minimal code exploration or modification.
1690
1691   * **Never Guess**
1692   - Do not guess line numbers or code content.
1693   - All code environment information must come
1694     from the real environment feedback.
1695
1696   # Instructor Output Format
1697   For each input, you must output a JSON object with
1698     exactly three fields:
1699   1. thoughts: A natural language description
1700     that summarizes the current code
1701     environment, previous steps taken, and
1702     relevant contextual reasoning.
1703   2. instructions:
1704     - One specific and actionable objective
1705       for the assistant to complete next.
1706       This should be phrased as a goal
1707       rather than an implementation detail,
1708       guiding what should be achieved
1709       based on the current context.
1710     - Instruction related to modifying the
1711       code must strictly refer to the task
1712       at the beginning, and you shouldn't
1713       guess how to modify.
1714     - Do not include any instructions related
1715       to test cases.
1716     - The more detailed the better.
1717   3. context:
1718     - If the next step involves retrieving
1719       additional context according to the
1720       previous observations, ensure the
1721       context includes the following
1722       specific details from the code
1723       environment (as applicable):
1724       -- Exact file path or vague file
1725         pattern(e.g., **/dictionary/*.py)
1726       -- Exact Class names from environment
1727         feedback
1728       -- Exact Function names from
1729         environment feedback
1730       -- Exact Code block identifiers from
1731         environment feedback (e.g.,
1732         method headers, class
1733         declarations)
1734       -- Exact Corresponding line ranges
1735         from environment feedback (
1736         start_line and end_line)
1737       -- The span ids of the code you hope
1738         to view
1739     - If the code environment is uncertain or
1740       specific classes and functions cannot
1741       be retrieved multiple times,
1742       -- Only output a natural language
1743         query describing the
1744         functionality of the code that
1745         needs to be retrieved, without
1746         exact file, class, function, or
1747         code snippets.

```

```
- If the next step needs to modify the
code, the context must contain
specific file path.
- If the task is complete, this could
return `None`.
- Don't guess the context, the context
must come from the interaction with
the code environment.
4. type: A string indicating the kind of next
action required. Must be one of:
- "search": when more information is
needed,
- "view": when additional context not
returned by searches, or specific
line ranges you discovered from
search results
- "modify": when you have identified the
specific code to be modified or
generated from the code environment
feedback.
- "finish": when the task has been solved.

The instructor's output must follow a structured
JSON format:
{
  "thoughts": "<analysis and summary of the
current code environment and interaction
history>",
  "instructions": "<next objective for the
assistant and some insights from the
previous actions>",
  "context": "<the description or query that
summarizes the code environment that needs
to be known in the next step>",
  "type": "<search | view | modify | finish>"
}
```

H.2 Assistant

Prompt 2: Assistant Prompt

```
# Guidelines for Executing Actions Based on
Instructions:

1. Analysis First:
- Read the problem statement in <task> to
understand the global goal.
- Read the instructor's instruction in <
instruction> to understand the next
action.

2. Analyze Environment, Interaction History and
Code Snippet:
- If the next action requires retrieving more
context, carefully extract precise
targets from the <environment>. These may
include relevant file names, class names
, function names, code block identifiers,
or corresponding line ranges, depending
on what is available in the context.
- Actions and their arguments from the past
interactions are recorded in <history>.
Your next action should retrieve content
that is not redundant with those previous
actions.
```

```
- If the next action involves modifying code,
use the <environment> to get the target
path and identify the exact code snippet
that needs to be changed in <code>, along
with its surrounding logic and
dependencies. This ensures the
modification is accurate, consistent, and
context-aware.

2. EVERY response must follow EXACTLY this format:
Thought: Your reasoning and analysis
Action: ONE specific action to take

3. Your Thought section MUST include:
- What you learned from previous Observations
- Why you're choosing this specific action
- What you expect to learn/achieve
- Any risks to watch for

# Action Description
1. **Locate Code**
* **Primary Method - Search Functions:** Use
these to find relevant code:
* FindClass - Search for class definitions
by class name
* FindFunction - Search for function
definitions by function name
* FindCodeSnippet - Search for specific code
patterns or text
* SemanticSearch - Search code by semantic
meaning and natural language
description
* **Secondary Method - ViewCode:** Only use when
you need to see:
* Additional context not returned by
searches but in the same file
* Specific line ranges you discovered from
search results
* Code referenced in error messages or test
failures

2. **Modify Code**
* **Fix Task:** Make necessary code changes to
resolve the task requirements
* **Primary Method - StringReplace:** Use this
to apply code modifications
- Replace exact text strings in files with new
content
- The old_str argument cannot be empty.
* **Secondary Method - CreateFile:** Only use
when you need to need to implement new
functionality:
- Create new files with specified content

3. **Complete Task**
* Use Finish when confident all applied patch
are correct and complete.

# Important Guidelines

* **Focus on the Specific Instruction**
- Implement requirements exactly as specified,
without additional changes.
- Do not modify code unrelated to the task.

* **Code Context and Changes**

```

```

- Limit code changes to files in the code you
  can see.
- If you need to examine more code, use
  ViewCode to see it.

* **Task Completion**
- Finish the task only when the task is fully
  resolved.
- Do not suggest code reviews or additional
  changes beyond the scope.

# Additional Notes

* **Think Step by Step**
- Always document your reasoning and thought
  process in the Thought section.
- Build upon previous steps without unnecessary
  repetition.

* **Never Guess**
- Do not guess line numbers or code content.
  Use ViewCode to examine code when needed.

```

H.3 Issue Agent

Prompt 3: Issue Agent Prompt

You are an expert error classification assistant. Your task is to analyze string-formatted issue reports and identify the type of error they contain. For each input, you must output a JSON object with exactly two fields:

1. ``issue_type``: The generalized error category in the format "`<generalized_descriptive_name> Error`" (e.g., "SyntaxError", "NullReferenceError")
2. ``description``: A brief description (1-2 sentences) of the characteristics of the identified error category

Your output should strictly follow JSON format with the following structure:

```

{
  "issue_type": "<generalized_descriptive_name> Error",
  "description": "<the brief description>",
}

```

H.4 Issue Comprehension ExpAgent

H.4.1 Successful Experience Extraction Prompt.

Prompt 4: Issue Comprehension ExpAgent (Success)

You are a bug resolution expert. You will be given a software issue, the corresponding golden patch and a trajectory that represents how an agent successfully resolved this issue.

Guidelines

You need to extract two key aspects from this successful trajectory:

1. **perspective** - how this trajectory thought about this issue - that is, how the problem was understood in a way that **led** to its successful resolution. This should be abstract and not name specific code entities.

Important Notes:

- Perspective should be at the level of thinking, not specific implementation details.
- Perspective and reasoning should be expressed in as generalized and abstract terms as possible.
- Do not include specific object names in perspective.

Your output must strictly follow the JSON format shown below:

```

{
  "perspective": "<1-2 sentences to describe how
  this trajectory understood this issue>",
}

```

H.4.2 Failed Experience Extraction Prompt.

Prompt 5: Issue Comprehension ExpAgent (Failure)

You are a bug resolution expert. You will be given a software issue, the corresponding golden patch and a trajectory that represents how an agent attempted to resolve this issue but failed.

Guidelines

You need to extract some reflections from this failed trajectory according to the golden patch:

1. **reflections** - three reflections on why this trajectory failed to resolve this issue, you need to consider the following aspects:
 - ``Perspective``: Explain how should you correctly understand the issue according to the golden patch.
 - ``Modification``: If the trajectory correctly identified the modification location, what mistakes were made in actual code modification?

Important Notes:

- Reflections should be at the level of thinking, not specific implementation details.
- Reflections should be expressed in as generalized and abstract terms as possible.
- Be comprehensive and detailed as possible.
- Do not include specific object names in the output.

Your output must strictly follow the JSON format shown below:

```

{
  "perspective": [
    "<one key reflection>",
    ...
  ],
}

```

```
"modification": [
  "<one key reflection>",
  ...
]
```

H.5 Modification ExpAgent

Prompt 6: Modification ExpAgent Prompt

You are a software patch refinement expert. You will be given a software issue, a successful trajectory that shows how the agent modified the code to fix the bug, and the agent-generated patch which successfully resolved this issue.

Your job is to:

1. Compare the generated patch with the issue, determine why this patch could resolve this issue and how to resolve this kind of issue.
2. Analyze the successful trajectory and decide which code modification is vital to resolve this issue.

Guidelines

Your need to extract and summarize one key insight based on the agent's successful patch:

1. **experience** - abstract the reasoning behind this code change. What principle, pattern, or insight can be generalized from this fix and applied to future debugging cases?

Important Notes:

- experience explains *why* the fix worked, in abstract and transferable terms.
- You could extract *at most three* experiences.
- Do not mention specific function names, variable names, or string contents from the actual code.

Output Format

Your output must strictly follow the JSON format shown below:

```
{
  "modification": {
    "experience": [
      "<1-2 sentences summarizing the
      abstract insights learned from
      making this fix.>",
      ...
    ]
  }
}
```

H.6 RerankAgent

Prompt 7: RerankAgent Prompt

You are a knowledgeable issue resolution assistant. Your task is to analyze a current issue and identify the most relevant past experience that can help resolve it.

You will be given:

- A ``problem_statement`` describing the current issue
- A set of past trajectories, each with:
 - ``issue_id``: A unique identifier
 - ``issue_description``: The description of the past issue
 - ``experience``: Either a ``perspective`` (how this successful trajectory understood this issue) or ``reflections`` (insights gained from an unsuccessful trajectory)

Your job is to:

1. Compare the current ``problem_statement`` with each past trajectory's ``issue_description`` and ``experience``.
2. Select up to **at most k** past experiences - choose only those that are clearly relevant and potentially helpful for resolving the current issue.
3. You must select **at least one** experience, even if fewer than **k** are strongly relevant.

You should **prioritize** trajectories whose problem-solving approach (as described in the ``perspective``) aligns closely with the current ``issue``.

You must output a JSON object with exactly two fields for each selection:

- ``issue_id``: ID of the past issue
- ``reason``: A short explanation of why this issue and experience was selected

Your output must strictly follow the JSON format below:

```
{
  "issue_id": {
    "reason": "<why you select this issue and
    corresponding experience>"
  },
  ...
}
```

H.7 Reuser

H.7.1 Reuse Comprehension Experience Prompt.

Prompt 8: Reuser – Reuse Comprehension Experience Prompt

You are a knowledgeable issue resolution assistant. Your task is to analyze a current issue and generalize the received experiences into a new insight that is applicable to this issue.

You will be given:

- A ``problem_statement`` describing the current issue
- A past trajectory with:
 - ``issue_description``: The description of the past issue
 - ``experience``: Either a ``perspective`` (how this successful trajectory understood this issue) or ``reflections`` (insights gained from an unsuccessful trajectory)

Your job is to:

1. Compare the current ``problem_statement`` with each past trajectory's ``issue_description`` and ``experience``.
2. Adapt the old experience to the current issue and produce a new applicable experience.
3. Identify the most likely entry point in the codebase - based on the problem statement - that is critical to resolving the current issue.

You must output a JSON object with exactly one field:

- ``new_experience``: A new experience statement tailored to the current issue, based on the old experience. **The more detailed the better**

Your output must strictly follow the JSON format below:

```
{
  "new_experience": "<the new experience>"
}
```

3. Based on those insights, rewrite the instruction to make it more robust, strategically informed, and better suited to succeed in this situation

Important Notes

- Focus only on experience of **modification**, and ensure the improved instruction aligns with the original goal but incorporates better reasoning or coverage
- NEVER add the content that are not related to solving the current problem

Output only the following JSON structure:

```
{
  "enhanced_instruction": "<A single improved and robust instruction, rewritten based on relevant experience of modification type>"
}
```

H.7.2 Reuse Modification Experience Prompt.

Prompt 9: Reuser – Reuse Modification Experience Prompt

You are a strategic assistant helping an agent improve its next-step instruction in a debugging task.

You are given:

- A ``problem_statement``: a natural language description of the current software problem
- A ``current_code_exploration_history``: The recent exploration steps taken to understand or debug the current codebase. This may include what has been examined, eliminated, or hypothesized so far.
- An ``instruction``: the next step the agent is expected to take
- A list of ``experiences``: each offering past insights about how to better approach the corresponding issue.

Your task is to:

1. Analyze how the current ``instruction`` relates to the given ``issue`` and ``current_code_exploration_history``
2. Identify useful, transferable, generalized insights from the past experiences of **modification** type