An Empirical Study on Strong-Weak Model Collaboration for Repo-level Code Generation

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Abstract

We study cost-efficient collaboration between strong and weak language models for repository-level code generation, where the weak model handles simpler tasks at lower cost, and the most challenging tasks are delegated to the strong model. While many works propose architectures for this task, few analyze performance relative to cost. We evaluate a broad spectrum of collaboration strategies: context-based, pipeline-based, and dynamic, on GitHub issue resolution. Our most effective collaborative strategy achieves equivalent performance to the strong model while reducing the cost by 40%. Based on our findings, we offer actionable guidelines for choosing collaboration strategies under varying budget and performance constraints. Our results show that strong-weak collaboration substantially boosts the weak model's performance at a fraction of the cost, pipeline and context-based methods being most efficient. We have also open-sourced the code [1] for our work.

1 Introduction

Recent advances in large language models (LLMs) have demonstrated impressive capabilities across complex reasoning and generation tasks. However, benchmark gains are often prioritized over practical deployment concerns, leading to systems that rely on repeated calls to expensive proprietary LLMs. For example, SWE-Agent (Yang et al., 2024) caps each run at $4 (Kapoor et al., 2024) , making even modest-scale evaluations prohibitively expensive. In contrast, systems such as Retrieval-Augmented Generation (RAG) can reduce cost by 99% (Jin et al., 2025), motivating a critical question: *How can we design effective yet cost-efficient LLM systems?* Retrieval-Augmented Code Generation (RACG) (Wang et al., 2025b) systems like Agentless (Xia et al., 2025) and Agentless Lite (Dunn, 2025) try to address this by selectively retrieving relevant context for generation, significantly reducing costs ($0.25 / run). However, varying task complexity necessitates hybrid setups where weak LLMs economically handle simpler tasks and escalate the rest. Yet, designing such systems is non-trivial because weak LLMs struggle with complexity, and overusing strong LLMs negates cost benefits.

While prior work explored strong-weak collaboration in NLP via LLM cascades (Chen et al., 2024b; Zhang et al., 2023; Yue et al., 2024), context augmentation (Chen et al., 2025b), ensembling (Zhang et al., 2024; Chen et al., 2024a), etc, a systematic analysis for repository level code generation remains unexplored.

To bridge this gap, we present a three-pronged taxonomy with 12 diverse strong-weak collaboration methods, including static context augmentation (e.g., Few-Shot examples, FAQs, Planning), pipeline division (e.g., Strong LM First, Prompt Reduction), and dynamic collaboration (e.g., Routing). Our taxonomy (Figure 1) draws on prior work along with tailored adaptations for code generation. We evaluate these methods across both API-based and hybrid (API + open-source) LLM pairs on the SWE-Bench Lite (Jimenez et al., 2024) benchmark. Our goal is to empirically characterize the cost-performance trade-offs of these methods and identify best practices under different budget and accuracy constraints. While issue-solving serves as a grounded and challenging testbed, our broader focus is on the general design space of strong–weak collaboration.

Our findings show that pipeline and context-based strategies offer the best average efficiency, while weak-only baselines consistently underperform. Yet, we find that examining average efficiency does not always predict optimal perfor-

[1] https://github.com/shubhamrgandhi/codegen-strong-weak-collab

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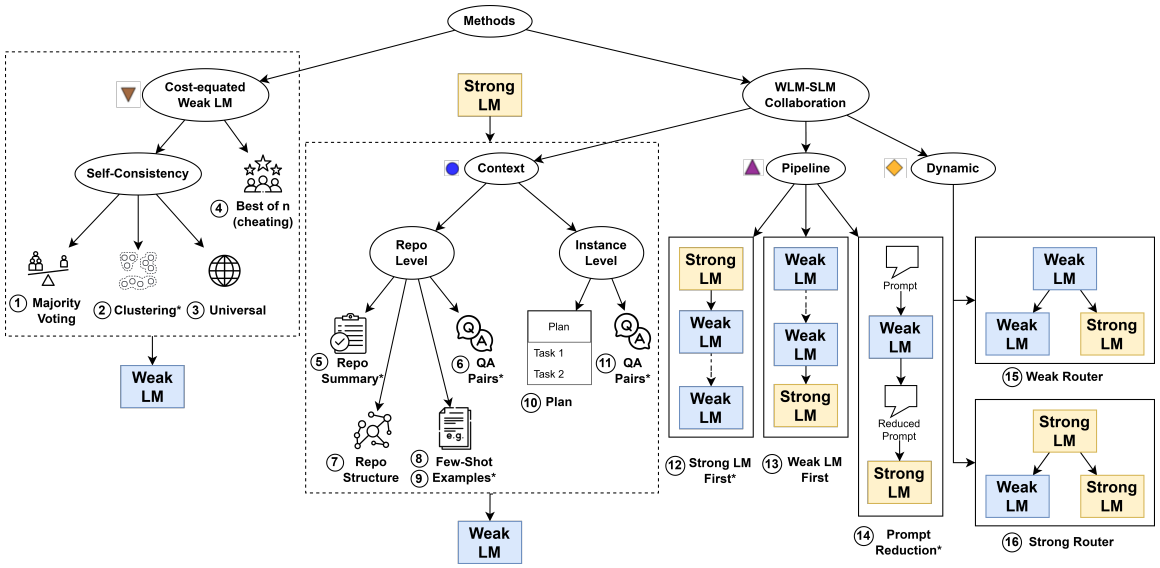

Figure 1: Taxonomy of the 14 techniques studied. * denotes methods newly proposed or adapted in this study. We categorize them into cost-equated weak-only, context-based, pipeline-based, and dynamic collaboration methods.

mance for a given cost. Through cost-performance curves, we answer the question: *What is the best method given a performance requirement and budget constraint?* Our best strategy improves the weak LLM's performance by ∼62%, almost matching the strong LLM, at ∼60% cost. Overall, we provide actionable principles for designing cost-efficient, collaborative LLM systems for complex code generation tasks in the future.

2 Related Work

2.1 Repository-Level Code Generation

Repository-Level Code Generation is a complex problem that requires LLMs to leverage the context of an entire repository and understand the structure and interleaving dependencies. The SWE-Bench benchmark (Jimenez et al., 2024) exemplifies this in the form of issue-resolution, a real-world repository-level code generation task, where the system must make edits to the code given an issue description and the relevant repository snapshot. This task can mainly be broken down into two sub-tasks: Fault Localization and Program Repair. Recent methods often use retrieval or structured pipelines to tackle this problem. For example, Retrieval Augmented Code Generation (RACG) frameworks first retrieve relevant code or documentation from the repository to aid in efficient fault localization before generation (Wang et al., 2025b; Li et al., 2025). While there exist agentic techniques like SWE-Agent (Yang et al., 2024) that are able to achieve a significant performance on this task, it often comes at a steep cost involving multiple calls to expensive LLMs. On the other hand, Agentless (Xia et al., 2025) entirely avoids multi-turn agent calls and instead sticks to a fixed three-step process involving localization, repair and validation, showing strong performance and low cost on SWE-Bench.

2.2 Cost reduction techniques for LLMs

Strong LLMs achieve high performance but are often too expensive to use at scale. To tackle this, several lines of work explore cost-efficient alternatives. Self-consistency (Wang et al., 2023; Chen et al., 2024c) aggregates multiple generations from the same LLM to improve performance. Other approaches rely on strong–weak collaboration. Amayuelas et al. (2025); Wang et al. (2025a) leverage a strong LM's superior reasoning capabilities to generate a plan for execution by a cheaper weak LM. Routing-based methods like FrugalGPT (Chen et al., 2024b) dynamically select LLMs to optimize cost and quality. Similarly, LLM Cascades (Yue et al., 2024) escalate to strong LMs only when weak LMs fail. Drawing from this, we curate a taxonomy of strong–weak collaboration strategies, including self-consistency, planning, LLM cascades (Weak LM First), routing among others, adapted to repository-level code generation. This allows us to empirically evaluate their cost-performance trade-offs in a unified framework.

3 Methodology

To conduct a systematic analysis, as shown in Figure 1, we present a taxonomy of strong-weak collaboration methods for repo-level RACG, where the methods are either based on or inspired by prior studies (Chen et al., 2025a; Bai et al., 2024; Xu et al., 2024; Lu et al., 2024; Chen et al., 2025c).

Preliminary. We conduct our experiments with Agentless-Lite (Dunn, 2025), a two-step repo-level RACG framework. We first apply a retriever to retrieve the top-k relevant documents (e.g., files in a repository) based on their similarity score with the query q. Then we apply an LM to iteratively generate the code with the documents as context until it is in the correct code patch format.

Cost-equated weak LM. We first study several baselines that *only* involve the weak LM (McDonald et al., 2025). Self-consistency (Wang et al., 2023) enhances weak LMs by sampling n diverse outputs, where $n \approx \text{Cost}_{strong}$ / Cost_{weak} and selecting the most consistent one via: ① Majority Voting (SC_m), ② Clustering (SC_c) and ③ Universal (SC_u). We also experiment on a "cheating" method, ④ Best of n. Detailed explanations are included in Appendix §A.1

Static Context Augmentation. We experiment methods that leverage the strong LM's superior problem-understanding capabilities to augment the context and use the weak LM for iterative generation to reduce cost. We first study methods that prompt the strong LM to generate repo-level information to provide background information for code generation, including: ⑤ Repository Summary, which generates a summary of the repository based on its `README` file and directory structure, ⑥ Repo-Level FAQs, which is similar but generates a set of FAQs instead, ⑦ Repo Structure, which summarizes the repository structure. Here we use RepoGraph (Ouyang et al., 2025) , which encodes the repository in a graph. We also study few-shot examples for each repository, which can be constructed by: ⑧ Few-shot (Random) that randomly selects k (input, successful strong LM output) pairs, and ⑨ Few-shot (Similarity), which selects few-shot demos based on the problem statements' embedding similarity. We also study methods that use the strong LM to generate instance-specific context. Compared to repo-level context, it typically requires a higher cost but provides more precise and example-relevant knowledge. We analyze: ⑩ Planning, which generates high-level planning for each instance (Amayuelas et al., 2025; Wang et al., 2025a), and ⑪ Instance-Level QA pairs, which generates a set of FAQs for each instance with the code generation query (e.g., issue description) and retrieved code as context.

Pipeline Division. These methods aim to reduce cost while maintaining performance by selectively calling the strong LM and weak LM sequentially as part of a hard-coded pipeline. Specifically, we compare: ⑫ Strong LM First, which prompts the strong LM to make the first attempt and calls the weak LM to iteratively refine its solution until it is correctly formatted. ⑬ Weak LM First, where the weak LM first makes n attempts to solve the issue, following model cascades (Chen et al., 2024b; Zhang et al., 2023; Yue et al., 2024). If it fails to generate a valid patch, the strong LM makes one attempt. Based on previous study's conclusion that weak LMs have comparable performance to strong LMs on localization (Xia et al., 2025), we present ⑭ Prompt Reduction, where we perform a preliminary call to the weak LM to reduce the code context by removing irrelevant code, thus reducing the overall context to be passed to the strong LM.

Dynamic Collaboration. Unlike §3, where the pipeline is hard-coded, we allow the decision to use the strong or weak model to be made dynamically during inference. Specifically, we invoke a router (Chen et al., 2024b) to decide if the problem is *simple* or *complex* and appropriately delegate it to the weak or strong LM. We evaluate both weak LMs and strong LMs as routers and denote them as ⑮ Weak Router and ⑯ Strong Router.

4 Experiments

Models. We consider strong-weak model pairs that have a noticeable gap in performance and cost, and the more expensive model performs better: **Strong LMs**: O3-mini, O4-mini (OpenAI, 2025) and GPT-4o-mini (OpenAI, 2024); **Weak LMs**: GPT-4o-mini and Qwen2.5-Coder series (Hui et al., 2024).

Dataset and Agentic Framework. We conduct all experiments on the SWE-bench Lite subset (Jimenez et al., 2024) which has 300 issues from 11 Python repositories. We run the Agentless Lite framework (Dunn, 2025) once per instance for our experiments, using `voyage-code-3`[2] for retrieval, techniques mentioned in §3 for generation (Details in Appendix §A.1).

[2] https://docs.voyageai.com/docs/embeddings

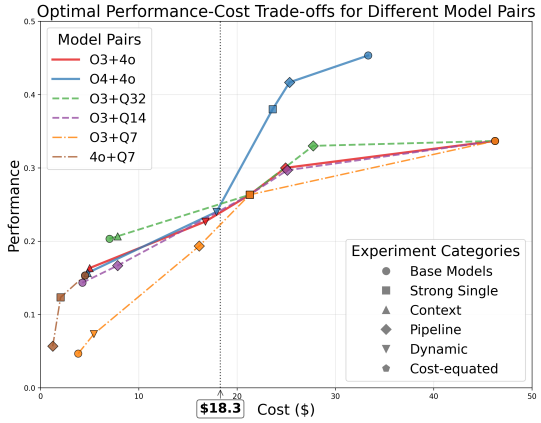

Figure 2: Performance vs. Cost curves for different Strong-Weak Model Pairs. O3 - O3-mini; O4 - O4-mini; 4o - GPT-4o-mini; Qx - Qwen2.5-Coder-xB. Detailed pairwise results in Appendix Figure 4 and Appendix Tables 3-8.

Evaluation Metrics. The following metrics are reported for each method: (1) *Resolution Rate*: Proportion of instances for which the generated patch successfully resolves the issue; and (2) *Cost*: Total generation cost ($) including additional method costs, but excluding retrieval cost, which remains constant across all methods.

5 Main Results

We focus our evaluation on the generator, as `voyage-code-3` achieves strong retrieval (∼92% recall, ∼76% MRR). Our findings uncover consistent patterns when strong–weak collaboration succeeds or fails (Appendix Figure 4, Appendix Tables 3-8.

Cost-equated baselines vs. Strong-Weak collaboration. As shown in Figure 2, Appendix Figure 4 and Appendix Tables 3-14 and Appendix Figure 4, across nearly all model pairs, the cost-equated baselines, i.e. sampling multiple times to match the strong LLM's cost, underperform compared to collaboration. Surprisingly, some baselines even hurt weak LLM's performance, which is likely due to faltering patch selection. Our best collaboration strategy, Strong LM First, achieves a 0.4167 resolution rate, which is ∼92% more than the best corresponding cost-equated baseline, i.e., best-of-n for GPT-4o-mini cost-equated with O4-mini.

Efficacy of Methods Across Taxonomy Groups. Analyzing by taxonomy (§3), on average, pipeline and context-based strategies yield the highest cost-efficiency across model pairs, followed by dynamic methods and *Best of n*, with self-consistency approaches being the least efficient (Appendix §A.3). However, average efficiency alone is not a reliable indicator of the best method. Performance–cost curves (Figure 2) often intersect, showing that Weak LM First is optimal when budget is low due to minimal strong LM usage, while Strong LM First dominates once budget increases. For example, with O3-mini + Qwen2.5-Coder-32B, Strong LM First achieves equivalent performance to the strong model at just ∼60% cost. We also observe a regime shift around the $18.3 mark as Figure 2 shows, below which O3 + Qwen2.5-Coder-32B performs best, whereas above it, O4 + GPT-4o-mini becomes more cost-effective.

These results suggest that no method is universally optimal. Instead, choosing the best strategy depends on the deployment scenario, specifically the available budget and required performance, which is enabled by plots like Figure 2. Given a minimum performance threshold and a budget cap, the optimal method corresponds to the curve that reaches the highest resolution rate within the feasible region i.e., the top-left quadrant defined by those constraints. For instance, if the target is at least 20% resolution within a $20 budget, *Weak Router* with O4-mini + GPT-4o-mini emerges as the most cost-effective choice. These observations yield actionable guidance: (1) Cost-equated weak-only methods are inefficient; (2) Pipeline-based methods outperform context-only methods when budget allows; (3) *Weak LM First* and *Weak Router* are strong choices under tight budgets; and (4) *Strong LM First* performs best in higher-budget regimes, often approaching strong LM performance at reduced cost.

5.1 Interesting cases

Instance-level help is better than repo-level help. Repo-level context (e.g., summaries, structure, QA pairs) consistently failed to improve weak LM performance. Such information is too coarse and may distract from instance-specific signals. Even few-shot examples, whether random or similar, often reduced accuracy. In contrast, instance-level augmentation (plans, QA pairs) significantly boosted resolution rates, justifying their higher cost.

Weak Router is better than Strong Router. Counterintuitively, *Weak Router* frequently outperformed *Strong Router*, both in accuracy and cost. For example, with O4-mini + Qwen2,5-Coder-32B, *Weak Router* achieved 6 percentage points higher

resolution at ∼20% lower cost. We suspect that stronger models , while good at problem solving, may "overthink" routing decisions (Cuadron et al., 2025). Only with very weak LMs (e.g., Qwen-7B) did strong routing slightly edge ahead, suggesting weak routing is often the more efficient choice.

Prompt Reduction trades turn-wise validity for overall performance. *Prompt Reduction* offers a surprising trade-off where it lowers the valid patch rate to ∼65%, which is well below the ∼95% average of other methods, yet often achieves higher resolution rates overall. Due to aggressive pruning of irrelevant context by the weak LM, the strong LM is forced to focus on the most salient code, leading to more successful fixes despite more retries. In effect, Prompt Reduction sacrifices turn-wise reliability in favor of sharper attention, making it a high-variance but high-upside strategy, especially when correctness matters more than efficiency.

6 Conclusion

We present a detailed taxonomy of strong-weak LLM collaboration techniques for repository-level code generation. Our results show substantial cost-efficiency gains with pipeline and context-based collaboration, maximizing average efficiency. However, no method is universally optimal, and the ideal choice depends on budget and performance constraints. We offer actionable principles for selecting when to prioritize weak models, apply dynamic routing, or escalate to hybrid pipelines. Our insights will help practitioners deploy accurate LLM systems aligned with realistic efficiency constraints. Future work can extend this taxonomy to more complex approaches and domains for improved cost-performance tradeoffs.

7 Acknowledgement

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8 Limitations and Potential Risk

For simplicity of experimentation, we restrict the scope of this study to Agentless Lite, a simple RAG + Code generation framework. However, we believe that the methods we consider are generalizable and simple enough to be extended to more complex architectures. We also limit the scope of this study to the code generation domain, however, parallels can easily be drawn to other domains and the methods can be tweaked to suit those applications. To curb costs for experimentation, we use the Lite subset of the SWE-Bench dataset. We focus the study only on inference-based approaches and do not consider any training or finetuning-related approaches since those often require expensive hardware setups which defeats the overall purpose of cost efficiency. We measure cost via Token / API usage and do not consider factors like latency or energy consumption since those would vary significantly with hardware. Potential risks of our work are similar to risks largely associated with LLM-based code generation in general. These include but are not limited to the methods studied being used to purposefully or inadvertently generate vulnerable or malicious code.

9 Scientific Artifacts

We use a variety of proprietary and open sourced LLMs for our study. We strictly use commercial APIs to access proprietary LLMs following the conditions outlined by the respective companies. We use an open source framework, Agentless Lite, for our experiments. We use the test set of the SWE-Bench Lite Benchmark for our experiments. To the best of our knowledge, it does not contains personally identifying information or offensive content.

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A Appendix

A.1 Hyperparameters and Implementation Details

We plan on open-sourcing our code soon. We set the `max_files` parameter for Agentless Lite to 5. For OpenAI's thinking models like O3-mini and O4-mini, we set the `reasoning_effort` parameter to `high`. We start the generation at a base temperature of `0.0`, which is gradually increased by `0.1` every time the model fails to generate a valid patch. We set the max number of retries as 10 for the base settings. All open-source model inferences were run using `vLLM` on 4 L40 GPUs, leveraging tensor parallelism for efficient distributed execution. We configured the server with `-tensor-parallel-size 4` and set `-gpu-memory-utilization 0.8` to optimize memory usage without overcommitment. Inference was performed in `bfloat16` precision with `-enforce-eager` execution to reduce kernel launch latency. To support long-context models, we enabled `chunked prefill` and set the `rope_scaling` parameter to use `YARN` with a factor of 4.0, extending support to sequences up to 32k tokens. Additional parameters included a maximum of 32,768 batched tokens, 8 concurrent sequences, and 16GB of CPU swap space to handle occasional memory spikes.

Cost-equated weak LM. We first study several baselines that *only* involve the weak LM (McDonald et al., 2025). Self-consistency (Wang et al., 2023) enhances weak LMs by sampling n diverse outputs, where $n \approx \text{Cost}_{strong}$ / Cost_{weak} and selecting the most consistent one via: ① Majority Voting (SC_m), where we select the most frequent patch, ② Clustering (SC_c), where we cluster the n candidate patches and select a patch at random from the largest cluster. We cluster the patches based on similarity calculated using `difflib.SequenceMatcher` ③ Universal (SC_u), where we follow Chen et al. (2024c) and prompt the weak LM itself to select the final patch. We also experiment on a "cheating" method, ④ Best of n, which checks whether any of the candidate patches is correct and serves as an upper bound for candidate selection methods.

Evaluation Metrics. The following metrics are reported for each method: (1) *Resolution Rate*: Proportion of instances for which the generated patch successfully resolves the issue; (2) *Average #Iterations*: The average number of calls made to strong and weak models, denoted by *s* and *w* respectively; (3) *Valid Patch Rate*: Fraction of instances for which the system was able to generate a patch that adheres to the required format; (4) *Cost*: Total generation cost ($) to process all 300 SWEBench-Lite instances, including additional method costs, but excluding retrieval cost, which remains constant across all methods, and (5) *Efficiency Score*: The ratio of Resolution Rate to Cost.

A.2 Prompts

A.2.1 Agentless Lite Base Prompt

```
We are currently solving the following
    issue within our repository. Here is
     the issue text:
--- BEGIN ISSUE ---
{problem_statement}
--- END ISSUE ---

Below are some code segments, each from
    a relevant file. One or more of
    these files may contain bugs:
--- BEGIN FILE ---
{retrieval}
--- END FILE ---

Please first localize the bug based on
    the issue statement, and then
    generate *SEARCH/REPLACE* edits to
    fix the issue.

Every *SEARCH/REPLACE* edit must use
    this format:
1. The file path
2. The start of search block: <<<<<<<
    SEARCH
3. A contiguous chunk of lines to search
     for in the existing source code
4. The dividing line: =======
5. The lines to replace into the source
    code
6. The end of the replace block: >>>>>>>
     REPLACE

Here is an example:

```python
### mathweb/flask/app.py
<<<<<<< SEARCH
from flask import Flask
=======
import math
from flask import Flask
>>>>>>> REPLACE
```

Please note that the *SEARCH/REPLACE*
    edit REQUIRES PROPER INDENTATION. If
     you would like to add the line '
          print(x)', you must fully
    write that out, with all those
    spaces before the code!
Wrap the *SEARCH/REPLACE* edit in blocks
     ```python...```.
```
```

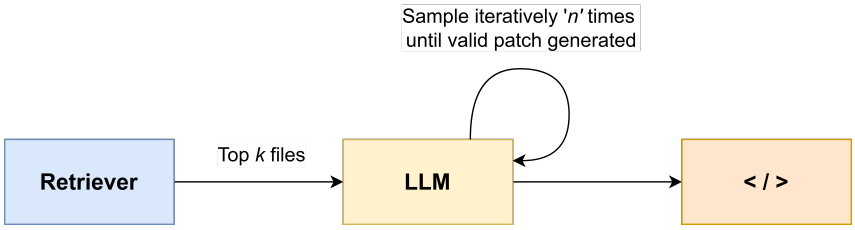


Figure 3: The Agentless Lite Framework: RAG + Code Generation

Experiment	Resolution Rate	Avg. #iterations	Valid Patch Rate	Total Generation Cost	Efficiency
o3-mini[1]	0.3367	1.83	0.977	46.224	0.0073
o4-mini[2]	**0.4533**	**1.32**	**0.993**	33.328	0.0136
claude-3.5-sonnet[3]	0.2667	2.13	0.957	**140.126**	0.0019
gpt-4o-mini[4]	0.1533	2.09	0.960	4.529	**0.0338**
qwen2.5-coder-7b[5]	0.0467	6.48	0.617	3.839*	0.0122
qwen2.5-coder-14b	0.1433	2.91	0.937	4.257*	0.0337
qwen2.5-coder-32b	0.2033	2.35	0.967	7.021*	0.0290
r1-distill-qwen-7b[6]	0.0033	9.91	0.013	115.161*	0.0000

[1] `o3-mini-2025-01-31` from https://platform.openai.com/docs/models/o3-mini
[2] `o4-mini-2025-04-16` from https://platform.openai.com/docs/models/o4-mini
[3] `claude-3-5-sonnet-20241022` from https://docs.anthropic.com/en/docs/about-claude/models/all-models
[4] `gpt-4o-mini-2024-07-18` from https://platform.openai.com/docs/models/gpt-4o-mini
[5] Qwen-2.5-Coder-Instruct series models from https://huggingface.co/Qwen
[6] `DeepSeek-R1-Distill-Qwen-7B` from https://huggingface.co/deepseek-ai/DeepSeek-R1-Distill-Qwen-7B

Table 1: Base performance of various models with Agentless Lite. Efficiency is calculated as resolution rate divided by generation cost. Models like `claude-3-5-sonnet-20241022` and `r1-distill-qwen-7b` are excluded from our main study due to poor cost-effectiveness. * - Estimated cost based on comparable API pricing.

A.2.2 Repo Summary

```
I need you to provide high-level
    insights about the following
    repository: {repo_name}

Based on the repository structure and
    README below, generate a
    comprehensive overview of this
    repository that could help guide a
    language model in solving technical
    issues.

Repository Structure:
{repo_structure}

README Content:
{readme_content}

Please provide the following insights.
    For each point, provide concrete
    details and specific examples from
    the codebase - high-level doesn't
    mean vague, it means providing a
    clear architectural overview with
    specific names, patterns, and
    implementations:

1. Core Purpose and Functionality:
    - What specific problem does this
        repository solve?
    - What are its primary features and
        capabilities?

2. Main Architectural Patterns:
    - Identify concrete architectural
        patterns used in this codebase
    - EXAMPLE: Plugin based architecture
        , layered architecture, etc

3. Module Organization:
    - Name the specific key modules and
        their exact responsibilities
    - EXAMPLE: I/O module, error-
        handling module, etc

4. Key Abstractions and Concepts:
    - List the actual fundamental
        abstractions used in the
        codebase
    - EXAMPLE: Quantity class for
        numerical values, Logger class
        for logging, etc

5. Design Patterns:
    - Identify specific recurring code
        patterns with examples
    - EXAMPLE: Factory methods,
        Decorators, etc

6. Error Handling Approaches:
    - Describe precise error handling
        mechanisms used in the codebase
    - EXAMPLE: Custom exception
        hierarchies, warnings, etc

Focus on providing actionable
    architectural insights that would be
```

```
     valuable for understanding the
    repository's design philosophy and
    core abstractions. Your response
    should contain specific
    implementation details that would
    help someone understand how to
    navigate, extend, and debug the
    codebase to solve issues.
```

A.2.3 Repo Level QA Pairs

```
I need you to generate a comprehensive
    FAQ about the repository: {repo_name
    }

Based on the repository structure and
    README below, create a detailed set
    of technical FAQs that would help a
    developer solve issues in this
    codebase. These FAQs should serve as
     guidance for someone who is trying
    to resolve bugs or implement new
    features.

Repository Structure:
{repo_structure}

README Content:
{readme_content}

Please generate 15-20 frequently asked
    questions with detailed answers
    about:

1. Code Organization and Architecture:
   - How is the codebase structured?
   - What are the key modules and their
       responsibilities?
   - How do the different components
       interact?

2. Common Patterns and Conventions:
   - What design patterns are commonly
       used?
   - What are the naming conventions and
        code style expectations?
   - Are there specific patterns for
       implementing new features?

3. Typical Debugging Approaches:
   - What are common error patterns and
       their solutions?
   - How to debug specific types of
       issues in this codebase?
   - What are common pitfalls when
       modifying this code?

4. Implementation Details:
   - How are core abstractions
       implemented?
   - What are the key algorithms or data
        structures used?
   - How does the error handling system
       work?

5. Testing Considerations:
   - How is testing typically done in
       this codebase?
   - What should be considered when
       writing tests?
   - Are there common test fixtures or
       utilities?

For each question, provide detailed,
    specific answers with concrete
    examples from the codebase when
    possible. Focus on information that
    would be most valuable to someone
    trying to fix bugs or implement new
    features. The FAQs should reflect
    the actual patterns and practices
    used in this specific repository,
    not generic software development
    advice.
```

A.2.4 Repo Structure

```
We are currently solving the following
    issue within our repository. Here is
     the issue text:
--- BEGIN ISSUE ---
{problem_statement}
--- END ISSUE ---

Below are some code segments, each from
    a relevant file. One or more of
    these files may contain bugs:
--- BEGIN FILE ---
{retrieval}
--- END FILE ---

To help you better understand the
    contexts of the code segments, we
    provide a set of dependencies of the
     code segments.
The dependencies reflect how the
    functions/classes in the code
    segments are referenced in the
    codebase.

--- BEGIN DEPENDENCIES ---
{dependencies}
--- END DEPENDENCIES ---

Please first localize the bug based on
    the issue statement, and then
    generate *SEARCH/REPLACE* edits to
    fix the issue.

Every *SEARCH/REPLACE* edit must use
    this format:
1. The file path
2. The start of search block: <<<<<<<
    SEARCH
3. A contiguous chunk of lines to search
     for in the existing source code
4. The dividing line: =======
5. The lines to replace into the source
    code
6. The end of the replace block: >>>>>>>
     REPLACE

Here is an example:

```python
### mathweb/flask/app.py
<<<<<<< SEARCH
```
```

```
from flask import Flask
=======
import math
from flask import Flask
>>>>>>> REPLACE
```

Please note that the *SEARCH/REPLACE* edit REQUIRES PROPER INDENTATION. If you would like to add the line 'print(x)', you must fully write that out, with all those spaces before the code!
Wrap the *SEARCH/REPLACE* edit in blocks ```python...```.

A.2.5 Few Shot Examples

```
Here are some {similar}example issues from the same repository along with the target file that were changed and final patch generated by an expert{successful}:
--- BEGIN EXAMPLES ---
{few_shot_examples}
--- END EXAMPLES ---

We are currently solving the following issue within our repository. Here is the issue text:
--- BEGIN ISSUE ---
{problem_statement}
--- END ISSUE ---

Below are some code segments, each from a relevant file. One or more of these files may contain bugs:
--- BEGIN FILE ---
{retrieval}
--- END FILE ---

Please first localize the bug based on the issue statement, and then generate *SEARCH/REPLACE* edits to fix the issue.

Every *SEARCH/REPLACE* edit must use this format:
1. The file path
2. The start of search block: <<<<<<< SEARCH
3. A contiguous chunk of lines to search for in the existing source code
4. The dividing line: =======
5. The lines to replace into the source code
6. The end of the replace block: >>>>>>> REPLACE

Here is an example:

```python
### mathweb/flask/app.py
<<<<<<< SEARCH
from flask import Flask
=======
import math
from flask import Flask
>>>>>>> REPLACE
```

Please note that the *SEARCH/REPLACE* edit REQUIRES PROPER INDENTATION. If you would like to add the line 'print(x)', you must fully write that out, with all those spaces before the code!
Wrap the *SEARCH/REPLACE* edit in blocks ```python...```.
```

A.2.6 Plan

```
We are currently solving the following issue within our repository. Here is the issue text:
--- BEGIN ISSUE ---
{problem_statement}
--- END ISSUE ---

Below are some code segments, each from a relevant file. One or more of these files may contain bugs:
--- BEGIN FILE ---
{retrieval}
--- END FILE ---

Please analyze the issue and provide a detailed plan to fix it. Do NOT generate any code patches or specific edits.

Your plan should include:

1. Bug localization: Identify which file(s) contain the bug based on the issue statement
2. Root cause analysis: Explain why the bug is occurring
3. Solution approach: Describe conceptually how to fix the issue
4. Implementation strategy: Outline the logical steps needed to implement the solution

Keep your analysis focused on the problem-solving approach rather than specific code changes.
```

A.2.7 Instance Level QA Pairs

```
We are currently solving the following issue within our repository. Here is the issue text:
--- BEGIN ISSUE ---
{problem_statement}
--- END ISSUE ---

Below are some code segments, each from a relevant file. One or more of these files may contain bugs:
--- BEGIN FILE ---
{retrieval}
--- END FILE ---

Please create a detailed FAQ (Frequently Asked Questions) document that would help a junior developer
```

```
    understand and fix this specific
    issue. Do NOT generate any code
    patches or specific edits.

Your FAQ should include 7-10 questions
    and answers about:

1. Issue Understanding:
   - What is the exact problem described
       in the issue?
   - What are the expected vs. actual
     behaviors?
   - What conditions trigger this issue?

2. Codebase Navigation:
   - Which specific files and functions
     are most relevant to this issue?
   - What are the key components
     involved in this functionality?
   - How do these components interact?

3. Technical Analysis:
   - What are the potential root causes
     of this issue?
   - What code patterns or anti-patterns
      might be contributing to the bug
     ?
   - What specific edge cases might not
     be handled correctly?

4. Implementation Guidance:
   - What approaches could be used to
     fix this issue?
   - What implementation pitfalls should
      be avoided?
   - How should the solution be tested?

5. Codebase Specifics:
   - What patterns or conventions does
     this codebase use that are
     relevant to the fix?
   - What existing helper functions or
     utilities could be leveraged?
   - What dependencies or side effects
     need to be considered?

Make your questions and answers detailed
    , specific to this issue, and
    include concrete references to the
    code when possible. Avoid generic
    programming advice - focus on
    information that directly helps
    solve this specific issue.
```

A.2.8 Prompt Reduction

```
We are currently solving the following
    issue within our repository. Here is
     the issue text:
--- BEGIN ISSUE ---
{problem_statement}
--- END ISSUE ---

Below are some code segments, each from
    a relevant file. One or more of
    these files may contain bugs:
--- BEGIN FILE ---
{retrieval}
--- END FILE ---

Your task is to identify the most
    relevant code sections that contain
    the bug or need to be modified to
    fix the issue.
Please output only the file paths and
    relevant code sections in this
    format:

### <file_path>
```python
# relevant code section 1
```

<file_path>
```python
# relevant code section 2
```

Only include the minimum necessary code
    with sufficient context to
    understand and fix the issue. Ensure
     that the code is complete and valid
     Python code.
Don't include any explanations or
    reasoning - just the file paths and
    code sections.
```

A.2.9 Weak / Strong Router

```
You are an expert software engineer
    tasked with analyzing software
    issues to determine the most
    efficient debugging approach.

Please analyze the following issue and
    codebase:

Issue description:
--- BEGIN ISSUE ---
{problem_statement}
--- END ISSUE ---

Relevant code:
--- BEGIN CODE ---
{retrieval}
--- END CODE ---

Your goal is to classify this issue as
    either SIMPLE or COMPLEX.

SIMPLE issues typically have these
    characteristics:
- Clear localization of the bug in the
    code
- Straightforward cause-effect
    relationship
- Relatively isolated impact (limited to
     one function or module)
- Common programming patterns or errors
- Solution likely follows established
    best practices

COMPLEX issues typically have these
    characteristics:
- Multiple components involved in the
    bug
- Subtle interactions between different
    parts of the codebase
```

```
- Requires deep reasoning about codebase
    architecture
- Edge cases that are difficult to
    identify
- May require creative or non-obvious
    solutions

Based solely on your analysis of the
    issue and code, respond with ONLY
    one of these two options:
- SIMPLE
- COMPLEX

Provide no explanation, reasoning, or
    additional text - just output the
    single classification word.
```

A.2.10 Universal Self-Consistency Patch Selection

```
I have generated the following {
    n_samples} potential solutions to
    fix this issue:

# Problem Statement
{problem_statement}

# Relevant Files
{formatted_files}

# Generated Solutions
{patches}

Based on the above solutions, select the
     most consistent and correct
    solution. Analyze the similarities
    and differences between the
    solutions, and select the one that
    best addresses the problem statement
     while making minimal and precise
    changes.

Your selection should be based on:
1. Correctness (does it solve the issue
    described in the problem statement)
2. Consensus (do multiple solutions
    agree on a similar approach)
3. Simplicity (does it make minimal
    necessary changes)

Return your selection as "SELECTED_PATCH
    : X" where X is the number of the
    chosen patch (1 to {n_samples}) and
    then explain your reasoning.
```

A.3 Statistical Analysis

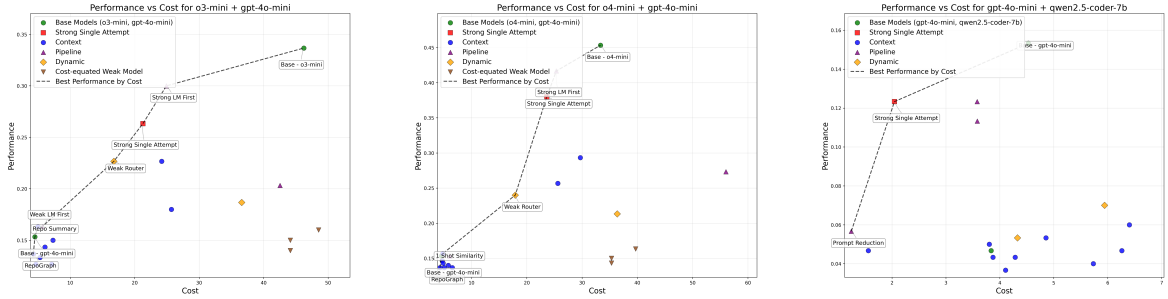
In order to systematically compare average efficiency, accuracy, and cost for 19 separate method configurations under 5 different method groups, we evaluated performance on SWE-Bench Lite over 6 strong-weak model pairs using 2 different ANOVA models for each of the 3 dependent measures, namely accuracy, efficiency, and cost.

For the first set of ANOVAs, we include Model Pair and Method Group as independent variables so that we can capture average trends while controlling for the effect of model pair. Both variables were highly significant in all three models ($p < .00001$), and each of the models captured between 66% and 80% of the variance in dependent measure, thus indicating that these models tell a meaningful story about what affects these dependent measures. For accuracy, Pipeline approaches were significantly better than all others. Self-Consistency and Context were significantly worse than all others. Best of n and Dynamic were in the middle. For cost, Self-Consistency and Best of n were significantly more than all others. Context was significantly cheaper than all others. And Pipeline and Dynamic were less than Self-Consistency and Best of n and more than Context. In terms of average efficiency, Pipeline and Context were significantly better than all others.

Taking a look at a higher level of granularity, we constructed a second set of ANOVAs shown in Appendix Table 2 with the specific methods rather than method groups. In this case, we see some overlap between groups of methods in terms of their accuracy, cost, and efficiency, but the general trends regarding the sets of methods are still very visible. Again, the two independent variables were highly significant in each model, and the amount of variance in dependent measure captured by the models ranged between 59% and 87%. For performance, Strong LM First and Strong LM Single Attempt were significantly higher than all others. In terms of cost, there were three separable groups, where the three Self-Consistency approaches, Prompt Reduction, and Strong Router were significantly higher than all others, followed by Plan, Instance level QA Pairs, Strong LM First, Strong LM Single Attempt, and Weak Router were significantly less expensive than those but significantly more expensive than the remaining methods. In terms of efficiency, Repo Structure is the best, but it is not significantly better than Weak LM First, Repo-Level QA Pairs, Strong LM Single Attempt, and Few shot (1 shot random and 1 shot similarity).

Level	Group	Least Sq Mean
Repo Structure	A	0.02818333
Weak LM First	A B	0.02365000
Repo Level QA Pairs	A B C	0.02128333
Strong LM Single Attempt	A B C	0.02100000
Few Shot Examples (1 Shot Random)	A B C D	0.02028333
Few Shot Examples (1 Shot Similarity)	A B C D E	0.01988333
Repo Summary	B C D E	0.01821667
Strong LM First	B C D E F	0.01640000
Few Shot Examples (5 Shot Similarity)	C D E F G	0.01501667
Few Shot Examples (5 Shot Random)	C D E F G	0.01483333
Weak Router	D E F G H	0.01170000
Prompt Reduction	E F G H	0.01135000
Plan	F G H	0.00801667
Instance Level QA Pairs	G H	0.00750000
Best of N	H	0.00605000
Strong Router	H	0.00585000
Self-Consistency – Clustering	H	0.00491667
Self-Consistency – Majority Vote	H	0.00486667
Self-Consistency – Universal	H	0.00475000

Table 2: Least Squares Mean Differences for Efficiency across Methods. Methods sharing a letter are not significantly different (Student's t, $\alpha = 0.05$, $t = 1.98667$).



(a) O3-mini (0.3367) + GPT-4o-mini (0.1533)

(b) O4-mini (0.4533) + GPT-4o-mini (0.1533)

(c) GPT-4o-mini (0.1533) + Qwen2.5-Coder-7B (0.0467)

(d) O3-mini (0.3367) + Qwen2.5-Coder-7B (0.0467)

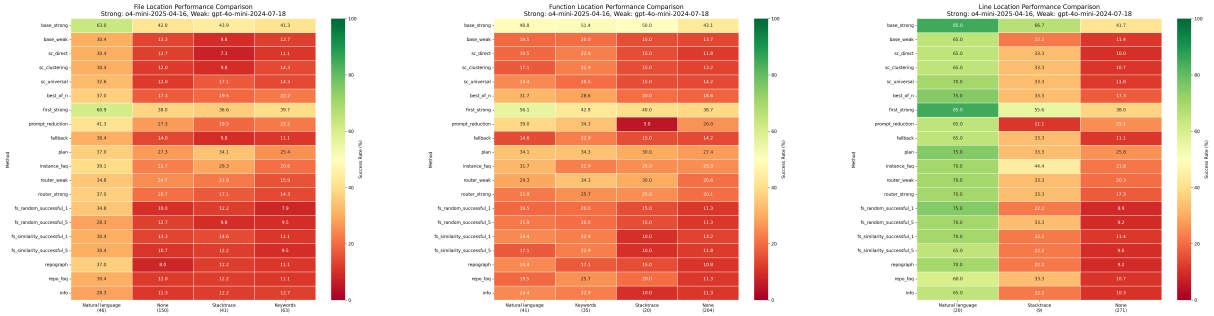
(e) O3-mini (0.3367) + Qwen2.5-Coder-14B (0.1433)

(f) O3-mini (0.3367) + Qwen2.5-Coder-32B (0.2033)

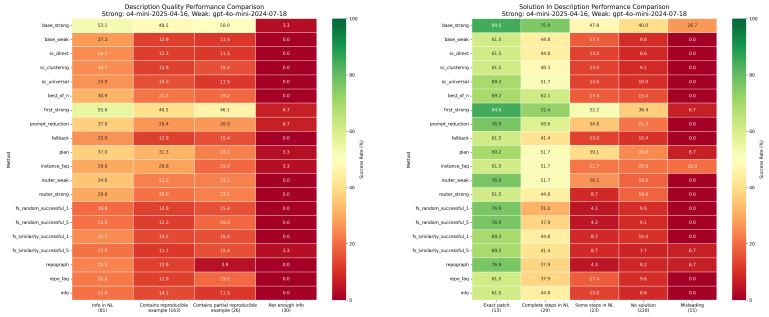
Figure 4: Performance vs. cost comparison across different Strong-Weak LM pairs, denoted as (Strong LM + Weak LM). The line denotes a monotonically increasing curve, i.e. what is the best method based on performance given a particular cost budget.

Experiment	Resolution Rate	Avg. #iterations	Valid Patch Rate	Total Generation Cost	Efficiency
Base - o4-mini	0.4533	**1.32s + 0.00w**	0.993	33.328	0.0136
Base - gpt-4o-mini	0.1533	0.00s + 2.09w	0.960	4.529	0.0338
Self-Consistency - Direct	**0.1433**	**0.00s + 15.58w**	**0.997**	35.307	0.0041
Self-Consistency - Clustering	0.1500	**0.00s + 15.58w**	**0.997**	35.307	0.0042
Self-Consistency - Universal	0.1633	**0.00s + 16.58w**	**0.997**	39.688	0.0041
Best of n (cheating)	0.2167	**0.00s + 15.58w**	**0.997**	35.307	0.0061
Plan	0.2933	**1.00s + 2.43w**	**0.897**	29.679	0.0099
Instance Level QA Pairs	0.2567	1.00s + 2.08w	**0.923**	25.598	0.0100
1 Shot Succesfull - Random	**0.1367**	**0.01s + 2.12w**	0.967	5.060	0.0270
5 Shot Succesfull - Random	**0.1400**	0.04s + 1.85w	0.977	5.793	0.0242
1 Shot Succesfull - Similarity	0.1567	0.01s + 1.99w	**0.957**	4.796	0.0327
5 Shot Succesfull - Similarity	**0.1367**	**0.04s + 2.15w**	**0.963**	6.520	0.0210
Repo Structure	**0.1367**	1.00s + 2.08w	**0.930**	4.288	0.0319
Repo Level QA Pairs	0.1467	1.00s + 1.92w	0.980	4.699	0.0312
Repo Summary	**0.1433**	1.00s + 2.02w	**0.957**	4.854	0.0295
Strong LM Single Attempt	0.3800	1.00s + 0.00w	0.793	23.616	0.0161
Strong LM First	0.4167	1.00s + 0.72w	0.960	25.341	0.0164
Prompt Reduction	0.2733	4.36s + 1.00w	**0.753**	**56.021**	0.0049
Weak LM First	0.1533	0.08s + 1.76w	0.977	6.061	0.0253
Weak Router	0.2400	**1.14s + 2.42w**	0.963	17.903	0.0134
Strong Router	0.2133	2.29s + 1.36w	0.967	36.342	0.0059

Table 3: Results with O4-mini as strong LM and GPT-4o-mini as weak LM. **Red** denotes drop. We consider a variance of 0.67% owing to the non-determinism introduced by the growing temperature values so a drop less than or equal to this is not marked in red.



(a) File Location (b) Function Location (c) Line Location



(d) Description Quality (e) Solution in Description

Figure 5: Heatmaps of issue category wise performance for O4-mini + GPT-4o-mini model pair.

Experiment	Resolution Rate	Avg. #iterations	Valid Patch Rate	Total Generation Cost	Efficiency
Base - o3-mini	0.3367	**1.83s + 0.00w**	**0.977**	46.224	0.0073
Base - gpt-4o-mini	0.1533	0.00s + 2.09w	0.960	4.529	**0.0338**
Self-Consistency - Direct	**0.1400**	**0.00s + 19.48w**	0.997	44.134	0.0032
Self-Consistency - Clustering	0.1500	**0.00s + 19.48w**	0.997	44.134	0.0034
Self-Consistency - Universal	0.1600	**0.00s + 20.48w**	0.997	**48.524**	0.0033
Best of n (cheating)	0.2200	**0.00s + 19.48w**	0.997	44.134	0.0050
Plan	0.2267	1.00s + 1.93w	**0.957**	24.182	0.0094
Instance Level QA Pairs	0.1800	1.00s + 2.01w	**0.943**	25.699	0.0070
1 Shot Succesfull - Random	**0.1333**	**0.01s + 2.19w**	**0.943**	5.323	0.0250
3 Shot Succesfull - Random	**0.1433**	**0.03s + 2.21w**	**0.940**	6.583	0.0218
5 Shot Succesfull - Random	**0.1267**	0.05s + 2.03w	0.963	7.127	0.0178
1 Shot Succesfull - Similarity	**0.1433**	**0.01s + 2.46w**	**0.923**	6.081	0.0236
3 Shot Succesfull - Similarity	**0.1367**	0.03s + 2.01w	**0.950**	6.093	0.0224
5 Shot Succesfull - Similarity	0.1500	**0.05s + 2.14w**	**0.947**	7.320	0.0205
1 Shot All - Random	0.1467	**0.00s + 2.35w**	**0.927**	5.716	0.0257
3 Shot All - Random	**0.1333**	**0.01s + 2.19w**	**0.937**	5.366	0.0248
5 Shot All - Random	0.1500	**0.02s + 2.10w**	**0.950**	5.712	0.0263
1 Shot All - Similarity	**0.1200**	**0.00s + 2.44w**	**0.923**	5.627	0.0213
3 Shot All - Similarity	**0.1367**	**0.01s + 2.37w**	**0.930**	5.959	0.0229
5 Shot All - Similarity	0.1500	**0.02s + 2.19w**	0.960	5.818	0.0258
Repo Structure	**0.1367**	1.00s + 2.08w	**0.930**	4.288	0.0319
Repo Level QA Pairs	**0.1267**	1.00s + 1.86w	0.977	4.686	0.0270
Repo Summary	0.1633	1.00s + 2.07w	0.960	5.000	0.0327
Strong LM Single Attempt	0.2633	1.00s + 0.00w	**0.690**	21.280	0.0124
Strong LM First	0.3000	1.00s + 1.17w	**0.930**	24.922	0.0120
Prompt Reduction	0.2033	4.73s + 1.00w	**0.653**	42.537	0.0048
Weak LM First	0.1633	0.08s + 1.61w	0.990	5.687	0.0287
Weak Router	0.2267	0.48s + 2.30w	0.977	16.764	0.0135
Strong Router	0.1867	1.71s + 1.22w	0.977	36.583	0.0051

Table 4: Results with O3-mini as strong LM and GPT-4o-mini as weak LM. **Red** denotes drop. We consider a variance of 0.67% owing to the non-determinism introduced by the growing temperature values so a drop less than or equal to this is not marked in red.

Experiment	Resolution Rate	Avg. #iterations	Valid Patch Rate	Total Generation Cost	Efficiency
Base - o3-mini	0.3367	**1.83s + 0.00w**	**0.977**	46.224	0.0073
Base - qwen2.5-coder-7b	0.0467	0.00s + 6.48w	0.600	3.839	0.0122
Self-Consistency - Direct	0.0733	**0.00s + 78.38w**	0.877	46.090	0.0016
Self-Consistency - Clustering	0.0700	**0.00s + 78.38w**	0.877	46.090	0.0015
Self-Consistency - Universal	0.0733	**0.00s + 79.38w**	0.877	**47.095**	0.0016
Best of n (cheating)	0.1033	**0.00s + 78.38w**	0.877	46.090	0.0022
Plan	0.0833	**1.00s + 6.79w**	**0.517**	24.092	0.0035
Instance Level QA Pairs	0.0767	1.00s + 6.95w	**0.563**	25.203	0.0030
1 Shot Succesfull - Random	0.0433	**0.01s + 6.49w**	0.617	4.281	0.0101
5 Shot Succesfull - Random	0.0433	**0.05s + 6.61w**	**0.590**	6.501	0.0067
1 Shot Succesfull - Similarity	**0.0367**	**0.01s + 6.63w**	0.603	4.282	0.0086
5 Shot Succesfull - Similarity	0.0433	**0.05s + 6.86w**	**0.570**	6.665	0.0065
Repo Structure	0.0500	**1.00s + 7.32w**	**0.487**	4.388	0.0114
Repo Level QA Pairs	0.0433	**1.00s + 6.75w**	**0.577**	4.676	0.0093
Repo Summary	0.0567	**1.00s + 6.70w**	**0.587**	9.139	0.0062
Strong LM Single Attempt	0.2633	1.00s + 0.00w	**0.690**	21.280	**0.0124**
Strong LM First	0.2633	1.00s + 2.66w	0.773	22.261	0.0118
Prompt Reduction	0.1867	4.56s + 1.00w	0.663	43.590	0.0043
Weak LM First	0.1933	0.62s + 3.82w	0.810	16.147	0.0120
Weak Router	0.0733	**0.07s + 7.42w**	0.607	5.432	0.0135
Strong Router	0.1033	1.77s + 3.72w	0.820	41.081	0.0025

Table 5: Results with O3-mini as strong LM and Qwen2.5-Coder-7B as weak LM. **Red** denotes drop. We consider a variance of 0.67% owing to the non-determinism introduced by the growing temperature values so a drop less than or equal to this is not marked in red.

Experiment	Resolution Rate	Avg. #iterations	Valid Patch Rate	Total Generation Cost	Efficiency
Base - o3-mini	0.3367	**1.83s + 0.00w**	0.977	46.224	0.0073
Base - qwen2.5-coder-14b	0.1433	0.00s + 2.91w	0.937	4.257	**0.0337**
Self-Consistency - Direct	0.1500	**0.00s + 32.59w**	**0.987**	48.249	0.0031
Self-Consistency - Clustering	0.1567	**0.00s + 32.59w**	**0.987**	48.249	0.0032
Self-Consistency - Universal	0.1500	**0.00s + 33.59w**	**0.987**	**51.069**	0.0029
Best of n (cheating)	0.2333	**0.00s + 32.59w**	**0.987**	48.249	0.0048
Plan	0.2233	**1.00s + 3.21w**	**0.893**	25.158	0.0089
Instance Level QA Pairs	0.1900	1.00s + 2.82w	**0.927**	25.599	0.0074
1 Shot Succesfull - Random	**0.1233**	**0.01s + 3.78w**	**0.863**	6.140	0.0201
5 Shot Succesfull - Random	**0.1033**	**0.05s + 4.15w**	**0.830**	8.641	0.0120
1 Shot Succesfull - Similarity	**0.1200**	**0.01s + 3.92w**	**0.880**	6.427	0.0187
5 Shot Succesfull - Similarity	**0.1233**	**0.05s + 3.97w**	**0.860**	8.713	0.0142
Repo Structure	0.1400	**1.00s + 3.04w**	**0.880**	4.393	0.0319
Repo Level QA Pairs	0.1400	**1.00s + 2.99w**	**0.907**	5.036	0.0278
Repo Summary	0.1467	**1.00s + 3.12w**	**0.930**	9.609	0.0153
Strong LM Single Attempt	0.2633	1.00s + 0.00w	**0.690**	21.280	0.0124
Strong LM First	0.2967	1.00s + 2.20w	**0.830**	25.099	0.0118
Prompt Reduction	0.2300	4.36s + 1.00w	**0.707**	40.568	0.0057
Weak LM First	0.1667	0.20s + 2.72w	**0.913**	7.847	0.0212
Weak Router	0.2400	1.34s + 2.45w	0.947	27.507	0.0087
Strong Router	0.1633	2.32s + 1.68w	0.937	39.201	0.0042

Table 6: Results with O3-mini as strong LM and Qwen2.5-Coder-14B as weak LM. **Red** denotes drop. We consider a variance of 0.67% owing to the non-determinism introduced by the growing temperature values so a drop less than or equal to this is not marked in red.

Experiment	Resolution Rate	Avg. #iterations	Valid Patch Rate	Total Generation Cost	Efficiency
Base - o3-mini	0.3367	**1.83s + 0.00w**	0.977	46.224	0.0073
Base - qwen2.5-coder-32b	0.2033	0.00s + 2.35w	0.967	7.021	0.0290
Self-Consistency - Direct	0.2133	**0.00s + 12.98w**	**0.987**	43.011	0.0050
Self-Consistency - Clustering	0.2133	**0.00s + 12.98w**	**0.987**	43.011	0.0050
Self-Consistency - Universal	0.2133	**0.00s + 13.98w**	**0.987**	**48.634**	0.0044
Best of n	0.2567	**0.00s + 12.98w**	**0.987**	43.011	0.0060
Plan	0.2533	**1.00s + 2.64w**	**0.913**	28.591	0.0089
Instance Level QA Pairs	0.2267	1.00s + 2.22w	**0.957**	27.700	0.0082
1 Shot Succesfull - Random	0.2067	**0.01s + 2.38w**	**0.957**	7.843	0.0264
5 Shot Succesfull - Random	**0.1800**	**0.05s + 2.35w**	**0.940**	10.426	0.0173
1 Shot Succesfull - Similarity	0.2033	**0.01s + 2.46w**	**0.947**	7.933	0.0256
5 Shot Succesfull - Similarity	0.2000	0.05s + 2.34w	0.967	9.583	0.0209
Repo Structure	**0.1700**	**1.00s + 2.63w**	**0.887**	5.302	**0.0321**
Repo Level QA Pairs	**0.1833**	1.00s + 2.33w	**0.950**	7.785	0.0235
Repo Summary	**0.1833**	**1.00s + 2.47w**	**0.933**	12.730	0.0144
Strong LM Single Attempt	0.2633	1.00s + 0.00w	**0.690**	21.280	0.0124
Strong LM First	0.3300	1.00s + 1.80w	**0.870**	27.737	0.0119
Prompt Reduction	**0.1600**	5.63s + 1.00w	**0.557**	54.735	0.0029
Weak LM First	0.2067	0.12s + 2.31w	**0.930**	8.9637	0.0231
Weak Router	0.2900	1.42s + 1.83w	0.970	32.772	0.0088
Strong Router	0.2300	2.31s + 1.50w	0.973	40.763	0.0056

Table 7: Results with O3-mini as strong LM and Qwen2.5-Coder-32B as weak LM. **Red** denotes drop. We consider a variance of 0.67% owing to the non-determinism introduced by the growing temperature values so a drop less than or equal to this is not marked in red.

Experiment	Resolution Rate	Avg. #iterations	Valid Patch Rate	Total Generation Cost	Efficiency
Base - gpt-4o-mini	**0.1533**	**2.09s + 0.00w**	**0.960**	4.529	0.0338
Base - qwen2.5-coder-7b	0.0467	0.00s + 6.48w	0.600	3.839	0.0122
Self-Consistency - Direct	0.0467	0.00s + 6.48w	0.600	3.839	0.0122
Self-Consistency - Clustering	0.0467	0.00s + 6.48w	0.600	3.839	0.0122
Self-Consistency - Universal	0.0467	0.00s + 6.48w	0.600	3.839	0.0122
Best of n (cheating)	0.0467	0.00s + 6.48w	0.600	3.839	0.0122
Plan	0.0467	**1.00s + 7.14w**	**0.483**	6.262	0.0075
Instance Level QA Pairs	0.0600	**1.00s + 6.99w**	**0.533**	**6.402**	0.0094
1 Shot Succesfull - Random	0.0500	**0.02s + 6.25w**	0.633	3.805	0.0131
5 Shot Succesfull - Random	0.0533	**0.10s + 6.90w**	**0.547**	4.854	0.0110
1 Shot Succesfull - Similarity	0.0433	**0.02s + 6.58w**	**0.590**	4.284	0.0101
5 Shot Succesfull - Similarity	0.0400	**0.10s + 6.79w**	**0.553**	5.733	0.0070
Repo Structure	0.0467	**1.00s + 7.42w**	**0.483**	1.562	0.0299
Repo Level QA Pairs	**0.0367**	**1.00s + 6.73w**	**0.563**	4.105	0.0089
Repo Summary	0.0433	**1.00s + 6.63w**	**0.570**	3.873	0.0112
Strong LM Single Attempt	0.1233	1.00s + 0.00w	0.693	2.046	**0.0603**
Strong LM First	0.1233	1.00s + 3.28w	0.770	3.579	0.0344
Prompt Reduction	0.0567	4.83s + 1.00w	0.647	1.246	0.0455
Weak LM First	0.1133	0.18s + 2.86w	0.823	3.581	0.0316
Weak Router	0.0533	**0.62s + 7.26w**	0.623	4.326	0.0123
Strong Router	0.0700	1.72s + 5.14w	0.723	5.941	0.0118

Table 8: Results with GPT-4o-mini as strong LM and Qwen2.5-Coder-7B as weak LM. **Red** denotes drop. We consider a variance of 0.67% owing to the non-determinism introduced by the growing temperature values so a drop less than or equal to this is not marked in red.

Method	File Precision	File Recall	File F1	Module Precision	Module Recall	Module F1	Line Precision	Line Recall	Line F1
Base Strong	84.23	84.23	84.23	84.23	84.23	84.23	55.13	47.33	48.43
Base Weak	78.65	78.82	78.7	78.65	78.82	78.7	35.92	28.49	29.97
Self-Consistency - Direct	76.92	76.92	76.92	76.92	76.92	76.92	35.56	27.74	29.21
Self-Consistency - Clustering	76.09	76.25	76.14	76.09	76.25	76.14	34.92	27.99	29.35
Self-Consistency - Universal	77.42	77.59	77.48	77.42	77.59	77.48	37.36	29.22	31.05
Best of N	76.25	76.25	76.25	76.25	76.25	76.25	36.55	29.11	30.34
Strong LM Single Attempt	80.5	81.6	80.84	80.5	81.6	80.84	50.94	44.05	44.76
Prompt Reduction	85.18	85.4	85.25	85.18	85.4	85.25	51.1	40.03	42.36
Weak LM First	77.82	77.82	77.82	77.82	77.82	77.82	37.4	30.17	31.41
Plan	85.5	86.62	85.87	85.5	86.62	85.87	49.7	44.09	43.99
Instance Level QA Pairs	83.57	84.12	83.75	83.57	84.12	83.75	49.5	40.7	41.74
Weak Router	79.87	80.28	79.99	79.87	80.28	79.99	42.78	37.03	37.43
Strong Router	80.17	80.34	80.23	80.17	80.34	80.23	43.08	36.01	36.91
1 Shot Succesfull - Random	77.93	77.93	77.93	77.93	77.93	77.93	34.93	25.86	28.02
5 Shot Succesfull - Random	78.16	78.16	78.16	78.16	78.16	78.16	36.14	28.47	29.87
1 Shot Succesfull - Similarity	78.22	78.4	78.28	78.22	78.4	78.28	35.89	28.8	29.95
5 Shot Succesfull - Similarity	78.2	78.2	78.2	78.2	78.2	78.2	38.7	29.47	31.64
Repo Structure	71.51	71.68	71.57	71.51	71.68	71.57	36.18	27.99	29.41
Repo Level QA Pairs	77.21	77.21	77.21	77.21	77.21	77.21	36.83	28.86	30.5
Repo Summary	76.25	76.66	76.36	76.25	76.66	76.36	36.24	28.64	30.23

Table 9: Localization performance for O4-mini as strong LM and GPT-4o-mini as weak LM. Cells highlighted in red depict lower score than the base weak LM setting.

Method	File Precision	File Recall	File F1	Module Precision	Module Recall	Module F1	Line Precision	Line Recall	Line F1
Base Strong	76.62	76.79	76.68	76.62	76.79	76.68	45.53	37.83	39.31
Base Weak	78.65	78.82	78.7	78.65	78.82	78.7	35.92	28.49	29.97
Self-Consistency - Direct	76.25	76.25	76.25	76.25	76.25	76.25	35.44	28.03	29.36
Self-Consistency - Clustering	75.75	75.92	75.81	75.75	75.92	75.81	35.63	28.31	29.76
Self-Consistency - Universal	76.25	76.25	76.25	76.25	76.25	76.25	35.44	28.03	29.36
Best of N	76.25	76.25	76.25	76.25	76.25	76.25	36.55	29.11	30.34
Strong LM Single Attempt	77.42	77.78	77.54	77.42	77.78	77.54	47.64	39.69	40.8
Prompt Reduction	83.16	83.67	83.33	83.16	83.67	83.33	49.25	39.14	41.03
Weak LM First	77.61	77.78	77.67	77.61	77.78	77.67	36.98	30.57	31.45
Plan	76.83	77.7	77.12	76.83	77.7	77.12	42.43	35.5	36.11
Instance Level QA Pairs	77.3	78.45	77.64	77.3	78.45	77.64	40.76	31.68	33.57
Weak Router	77.82	77.82	77.82	77.82	77.82	77.82	39.14	34.35	34.48
Strong Router	73.04	73.38	73.15	73.04	73.38	73.15	36.1	30.54	31
1 Shot Succesfull - Random	77.03	77.39	77.15	77.03	77.39	77.15	34.57	27.75	28.94
5 Shot Succesfull - Random	74.05	74.05	74.05	74.05	74.05	74.05	34.8	26.91	28.44
1 Shot Succesfull - Similarity	75.71	75.89	75.77	75.71	75.89	75.77	33.72	25.96	27.34
5 Shot Succesfull - Similarity	77.78	77.78	77.78	77.78	77.78	77.78	35.61	27.96	29.25
Repo Structure	71.51	71.68	71.57	71.51	71.68	71.57	36.18	27.99	29.41
Repo Level QA Pairs	75.6	75.77	75.65	75.6	75.77	75.65	36.48	29.27	30.43
Repo Summary	77.95	78.12	78.01	77.95	78.12	78.01	36.31	29.31	30.26

Table 10: Localization performance for O3-mini as strong LM and GPT-4o-mini as weak LM. Cells highlighted in red depict lower score than the base weak LM setting.

Method	File Precision	File Recall	File F1	Module Precision	Module Recall	Module F1	Line Precision	Line Recall	Line F1
Base Strong	76.62	76.79	76.68	76.62	76.79	76.68	45.53	37.83	39.31
Base Weak	76.11	76.11	76.11	76.11	76.11	76.11	24.56	19.66	19.95
Self-Consistency - Direct	71.48	71.48	71.48	71.48	71.48	71.48	23.65	17.86	18.77
Self-Consistency - Clustering	72.24	72.24	72.24	72.24	72.24	72.24	23.61	18.02	18.9
Self-Consistency - Universal	71.48	71.48	71.48	71.48	71.48	71.48	23.65	17.86	18.77
Best of N	71.86	71.86	71.86	71.86	71.86	71.86	24.08	18.62	19.36
Strong LM Single Attempt	79.31	79.74	79.45	79.31	79.74	79.45	47.91	40.23	41.19
Prompt Reduction	75.04	75.88	75.29	75.04	75.88	75.29	42.84	34.8	36.01
Weak LM First	77.16	77.37	77.23	77.16	77.37	77.23	36.93	31.54	31.44
Plan	77.74	78.06	77.85	77.74	78.06	77.85	39.95	33.04	33.55
Instance Level QA Pairs	81.07	81.07	81.07	81.07	81.07	81.07	35.08	27.67	28.41
Weak Router	77.47	77.47	77.47	77.47	77.47	77.47	26.06	22.34	22.47
Strong Router	69.92	70.33	70.05	69.92	70.33	70.05	26.3	21.71	22.35
1 Shot Succesfull - Random	74.73	74.73	74.73	74.73	74.73	74.73	22.32	16.92	17.54
5 Shot Succesfull - Random	74.01	74.01	74.01	74.01	74.01	74.01	19.89	17	16.92
1 Shot Succesfull - Similarity	67.96	67.96	67.96	67.96	67.96	67.96	22.29	16.2	17.9
5 Shot Succesfull - Similarity	71.93	71.93	71.93	71.93	71.93	71.93	24.24	19.16	20.12
Repo Structure	69.86	69.86	69.86	69.86	69.86	69.86	32.96	25.97	27.28
Repo Level QA Pairs	73.12	73.41	73.22	73.12	73.41	73.22	23.76	18.12	18.87
Repo Summary	73.48	73.86	73.58	73.48	73.86	73.58	24.31	19.55	20.01

Table 11: Localization performance for O3-mini as strong LM and Qwen2.5-Coder-7B as weak LM. Cells highlighted in red depict lower score than the base weak LM setting.

Method	File Precision	File Recall	File F1	Module Precision	Module Recall	Module F1	Line Precision	Line Recall	Line F1
Base Strong	76.62	76.79	76.68	76.62	76.79	76.68	45.53	37.83	39.31
Base Weak	74.67	75.8	75.03	74.67	75.8	75.03	37.41	30.85	32.01
Self-Consistency - Direct	76.35	76.35	76.35	76.35	76.35	76.35	38.41	29.98	32
Self-Consistency - Clustering	76.13	76.35	76.18	76.13	76.35	76.18	38.13	30.16	31.91
Self-Consistency - Universal	76.35	76.35	76.35	76.35	76.35	76.35	38.41	29.98	32
Best of N	75	75	75	75	75	75	37.24	29.15	30.97
Strong LM Single Attempt	83.13	83.53	83.27	83.13	83.53	83.27	51.72	42.03	43.96
Prompt Reduction	77.59	78.3	77.83	77.59	78.3	77.83	43.74	35.83	37.21
Weak LM First	76.64	77.37	76.89	76.64	77.37	76.89	38.25	31.28	32.62
Plan	74.22	76.12	74.78	74.22	76.12	74.78	42.65	35.47	36.35
Instance Level QA Pairs	79.26	80.94	79.8	79.26	80.94	79.8	42.5	36.41	37.05
Weak Router	77.46	77.82	77.58	77.46	77.82	77.58	40.91	34.46	35.13
Strong Router	75.09	75.8	75.33	75.09	75.8	75.33	37.09	30.98	31.79
1 Shot Succesfull - Random	76.77	77.61	77.03	76.77	77.61	77.03	31.97	25.69	26.77
5 Shot Succesfull - Random	72.82	73.49	73.03	72.82	73.49	73.03	31.04	23.6	24.89
1 Shot Succesfull - Similarity	72.92	73.48	73.11	72.92	73.48	73.11	31.38	24.39	25.89
5 Shot Succesfull - Similarity	72.16	72.87	72.35	72.16	72.87	72.35	32.34	25.15	26.51
Repo Structure	69.7	70.45	69.95	69.7	70.45	69.95	37.79	30.11	31.57
Repo Level QA Pairs	77.39	77.94	77.57	77.39	77.94	77.57	34.48	28.5	29.36
Repo Summary	75.09	75.27	75.15	75.09	75.27	75.15	34.87	28.8	29.62

Table 12: Localization performance for O3-mini as strong LM and Qwen2.5-Coder-14B as weak LM. Cells highlighted in red depict lower score than the base weak LM setting.

Method	File Precision	File Recall	File F1	Module Precision	Module Recall	Module F1	Line Precision	Line Recall	Line F1
Base Strong	76.62	76.79	76.68	76.62	76.79	76.68	45.53	37.83	39.31
Base Weak	76.9	78.28	77.36	76.9	78.28	77.36	41.65	34.76	35.46
Self-Consistency - Direct	78.63	79.73	78.96	78.63	79.73	78.96	42.58	34.75	35.76
Self-Consistency - Clustering	79.31	80.41	79.64	79.31	80.41	79.64	43.16	35.34	36.33
Self-Consistency - Universal	78.63	79.73	78.96	78.63	79.73	78.96	42.58	34.75	35.76
Best of N	78.63	80.07	79.08	78.63	80.07	79.08	42.78	34.72	35.87
Strong LM Single Attempt	79.31	79.31	79.31	79.31	79.31	79.31	51.91	43.96	45.32
Prompt Reduction	73.35	73.65	73.45	73.35	73.65	73.45	46.04	36.86	38.79
Weak LM First	76.7	77.06	76.82	76.7	77.06	76.82	42.05	34.32	35.48
Plan	75.55	79.2	76.76	75.55	79.2	76.76	44.5	39.48	39.15
Instance Level QA Pairs	76.54	78.05	77	76.54	78.05	77	45.86	39.95	39.82
Weak Router	75.6	75.95	75.72	75.6	75.95	75.72	47.65	37.9	40.02
Strong Router	74.23	75.34	74.57	74.23	75.34	74.57	42.13	35.18	36.14
1 Shot Succesfull - Random	78.86	80.14	79.27	78.86	80.14	79.27	42.43	35.69	36.2
5 Shot Succesfull - Random	75.53	76.6	75.89	75.53	76.6	75.89	41.6	34.84	35.34
1 Shot Succesfull - Similarity	75.95	77.11	76.29	75.95	77.11	76.29	43.71	36.77	37.27
5 Shot Succesfull - Similarity	76.79	77.59	77.01	76.79	77.59	77.01	41.71	35.02	35.48
Repo Structure	71.99	72.93	72.31	71.99	72.93	72.31	40.63	34.8	35.62
Repo Level QA Pairs	77.49	79.65	78.19	77.49	79.65	78.19	41.87	37.01	36.43
Repo Summary	75.83	77.14	76.25	75.83	77.14	76.25	41.64	34.88	35.3

Table 13: Localization performance for O3-mini as strong LM and Qwen2.5-Coder-32B as weak LM. Cells highlighted in red depict lower score than the base weak LM setting.

Method	File Precision	File Recall	File F1	Module Precision	Module Recall	Module F1	Line Precision	Line Recall	Line F1
Base Strong	78.65	78.82	78.7	78.65	78.82	78.7	35.92	28.49	29.97
Base Weak	76.11	76.11	76.11	76.11	76.11	76.11	24.56	19.66	19.95
Self-Consistency - Direct	71.48	71.48	71.48	71.48	71.48	71.48	23.65	17.86	18.77
Self-Consistency - Clustering	72.24	72.24	72.24	72.24	72.24	72.24	23.61	18.02	18.9
Self-Consistency - Universal	71.48	71.48	71.48	71.48	71.48	71.48	23.65	17.86	18.77
Best of N	71.86	71.86	71.86	71.86	71.86	71.86	24.08	18.62	19.36
Strong LM Single Attempt	78.14	78.35	78.21	78.14	78.35	78.21	38.13	32.03	33.06
Prompt Reduction	70.88	71.13	70.96	70.88	71.13	70.96	31.91	23.21	24.78
Weak LM First	77.73	77.73	77.73	77.73	77.73	77.73	33.98	27.07	28.62
Plan	84.37	84.83	84.48	84.37	84.83	84.48	37.48	29.69	31.28
Instance Level QA Pairs	77.19	77.5	77.29	77.19	77.5	77.29	32.2	26.17	26.87
Weak Router	75.4	75.4	75.4	75.4	75.4	75.4	23.26	18.98	19.08
Strong Router	74.04	74.65	74.19	74.04	74.65	74.19	24.98	19.89	20.59
1 Shot Succesfull - Random	75.79	75.79	75.79	75.79	75.79	75.79	18.15	12.72	14.01
5 Shot Succesfull - Random	72.56	72.56	72.56	72.56	72.56	72.56	23.67	17.08	18.6
1 Shot Succesfull - Similarity	71.75	71.75	71.75	71.75	71.75	71.75	20.17	17.15	17.06
5 Shot Succesfull - Similarity	72.89	72.89	72.89	72.89	72.89	72.89	21.59	15.72	17.12
Repo Structure	68.97	68.97	68.97	68.97	68.97	68.97	29.55	22.8	24.31
Repo Level QA Pairs	75.74	75.74	75.74	75.74	75.74	75.74	22.34	16.72	17.79
Repo Summary	76.61	76.61	76.61	76.61	76.61	76.61	24.02	18.62	19.21

Table 14: Localization performance for GPT-4o-mini as strong LM and Qwen2.5-Coder-7B as weak LM. Cells highlighted in red depict lower score than the base weak LM setting.