DISCOVERING HIERARCHICAL SOFTWARE ENGINEERING AGENTS VIA BANDIT OPTIMIZATION

Anonymous authors
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ABSTRACT

Large language models (LLMs) are increasingly applied to software engineering (SWE), but they struggle on real-world tasks that are long-horizon and often out of distribution. Current systems typically adopt monolithic designs where a single model attempts to interpret ambiguous issues, navigate large codebases, and implement fixes in one extended reasoning chain. This design makes it difficult to generalize beyond training data. Inspired by how human engineers decompose problems into sub-tasks, we argue that SWE agents should be structured as orchestrators coordinating specialized sub-agents, each responsible for a specific sub-task such as bug reproduction, fault localization, code modification, or validation. The central challenge is how to design these hierarchies effectively. Manual decompositions follow human workflows but often mismatch LLM capabilities, while automated search methods such as evolutionary strategies require evaluating a very large number of candidates, making them prohibitively expensive for SWE. We show that formulating hierarchy discovery as a multi-armed bandit problem enables efficient exploration of sub-agent designs under limited budgets. On SWE-bench-Verified, this approach outperforms single-agent systems and manually designed multi-agent systems. On SWE-bench-Live, which features recent and out-of-distribution issues, our system ranks 2nd on the leaderboard with a 36B model, surpassing larger systems such as GPT-4 and Claude. This provides the first evidence that hierarchical multi-agent systems improves generalization on challenging long-horizon SWE tasks.

1 INTRODUCTION

Large language models (LLMs) have achieved remarkable progress in natural language processing [41] and reasoning [18], and are increasingly adopted in solving complex coding problems [61]. Yet solving real-world software engineering (SWE) problems remains challenging [24] for LLMs, particularly for issues that fall outside the training distribution [58]. Despite strong results on SWE-bench-Verified [24], state-of-the-art systems struggle on more recent and out-of-distribution issues in SWE-bench-Live [58].

One possible cause is the long-horizon nature of SWE tasks: Current LLM agents typically rely on a single model to interpret underspecified problem statements, navigate large and interdependent codebases, and carry out all sub-tasks—reproducing the bug, localizing the fault, editing the code, and validating the fix—within *one* extended reasoning chain. This monolithic design hinders generalization: long contexts dilute attention and reduce retrieval accuracy [38; 39; 21], while jointly solving all sub-tasks prevents modularity and hinders robustness [59; 60].

Inspired by how human engineers approach complex problems, we posit that explicit hierarchy can help LLM-based agents manage long workflows. Cognitive science shows that people reduce mental effort by decomposing tasks into smaller sub-tasks [31; 40; 33]; in software engineering, this typically involves bug reproduction, fault localization, code modification, and validation [49; 23; 29]. This same idea appears as temporal abstraction in hierarchical reinforcement learning (HRL) [10]: instead of solving everything step by step, problems are handled by delegating to reusable sub-agents, each defined as a policy for a specific sub-task [44]. An orchestrator coordinates these sub-agents by choosing which one to activate, and each runs until it finishes its sub-task [44; 16; 9]. By planning with sub-agents rather than individual steps, the orchestrator shortens the reasoning horizon, which

reduces distraction from irrelevant details and isolates reusable patterns. This not only makes complex problems more manageable but also improves generalization, since effective sub-agents can be reused across different tasks and contexts.

Approaches to hierarchical multi-agent system design range from manual to automated. At one end, engineers manually design decompositions, specifying sub-tasks and sub-agents that follow human workflows [8; 35; 11]. These designs require substantial effort, and workflows that are natural for humans do not necessarily translate into effective performance on LLM agents as shown in our experiments (Section 5). At the other end, automated methods such as evolutionary search generate designs automatically [56; 25; 22], but require evaluating large numbers of candidates. This is practical in domains with cheap evaluation, such as multi-hop question answering [53; 30], but infeasible for software engineering (SWE). In SWE, evaluations are *expensive* and *long-horizon*: validating a single design can take up to an hour, requiring multi-step sandboxed runs and full integration tests. The difficulty of *credit assignment* [42; 36] makes this even worse: determining which sub-agents actually contributed to success would typically require extensive sampling, which is prohibitively costly.

To address these challenges, we draw inspiration from multi-armed bandit (MAB) [14; 1; 17; 54] and formulate the design of hierarchical multi-agent systems as a sequential decision-making process. We term our method *Bandit Optimization for Agent Design (BOAD)*. In MAB problems, a learner must identify the best arm from a pool with limited performance queries, where outcomes are stochastic. The learner balances exploration (testing new or uncertain arms) with exploitation (selecting the arm with the highest observed reward so far). In our setting, each arm corresponds to a sub-agent design (i.e., an agent prompt). We first optimize sub-agents and then fix them before deriving an orchestrator design using LLM prompting, since jointly optimizing both would be a costly bi-level optimization problem [13]. Typical evolutionary algorithms [20] generate candidate designs, evaluate them, discard them, and propose new ones by mutating the top performers. This process is wasteful: useful sub-agents may be discarded and rarely rediscovered because evolution is stochastic. Instead, we archive all generated designs, and adaptively choose promising combinations to evaluate next. This ensures efficient reuse of past designs and increases the likelihood of retaining strong sub-agents. To tackle the credit assignment problem, we go beyond binary success signals of entire sub-agent sets. We use LLM-as-a-judge [27] to assess whether individual sub-agents contributed meaningfully within a trajectory and use these "helpfulness" scores as rewards for the model selection algorithm.

We evaluate our BOAD on SWE-bench-Verified [24], a benchmark for software engineering tasks grounded in real GitHub issues. On SWE-bench-Verified, our method consistently outperforms single-agent systems and manually designed multi-agent systems. On SWE-bench-Live [28], which includes more recently collected issues and presents out-of-distribution challenges, our system achieves **2nd place** on the leaderboard using a 36B model—outperforming larger-scale systems based on Claude and GPT-4. To our best knowledge, our work is the first to show generalization improvements using automatically discovered hierarchical multi-agent systems on challenging long-horizon interactive tasks like SWE-bench.

2 Related works

Meta-agent design. Recent research has explored automatically designing agent organizations to reduce reliance on human intuition. Zhang et al. [56]; Hu et al. [22] propose frameworks for workflow generation and system-level automation, while Kim et al. [25] use evolutionary strategies for self-referential prompt refinement. Chen et al. [12] dynamically constructs role-based agents and coordinates them per task, though these roles are ephemeral and not reusable across settings. Other approaches, such as Misaki et al. [32], improve inference-time compute allocation by adaptively deciding whether to explore new candidates or refine existing ones. However, a common limitation of these meta-agent design methods is their reliance on frequent evaluations to guide search. They perform well when feedback is cheap and abundant (e.g., reasoning benchmarks or simple QA tasks), but become impractical in software engineering settings, where each candidate often requires sandboxed execution or full unit testing. In contrast, our method evolves reusable sub-agents and an orchestrator, reusing effective components to reduce redundant evaluations and maintain efficiency even under expensive feedback conditions.

Evolutionary strategies for LLMs. Evolutionary strategies has been applied broadly to improve LLM-based systems, such as algorithm discovery via code mutation [34] and self-rewriting agents that iteratively mutate their own source code [55]. Evolutionary strategies have also been widely explored for prompt optimization: Kim et al. [25] use co-evolutionary refinement, Guo et al. [19] apply genetic search to discrete prompt tokens, and Agrawal et al. [2] leverage reflection with Pareto-based selection for sample-efficient instruction tuning. These methods highlight how evolution can reduce human effort and uncover novel strategies, but they typically rely on abundant, inexpensive evaluations. In contrast, our method targets costly, long-horizon SWE tasks by maintaining a reusable archive of sub-agents and casting sub-agent selection as a multi-armed bandit problem, improving sample efficiency while preserving the benefits of hierarchical organization.

Multi-agent systems for SWE. Prior work has explored multi-agent designs for software engineering tasks. Arora et al. [8]; Phan et al. [35]; Chen et al. [11] adopt modular or graph-based pipelines, where subtasks and agent roles are manually defined. While structured, such pipelines require heavy engineering and often fail to generalize. Other works exploit agent diversity through fixed coordination schemes. Li et al. [28] engages specialized agents in a multi-round debate over candidate bug-fix plans before producing the final repair, while Zhang et al. [57] introduce a meta-policy that aggregates the code patch from multiple agents and identifies the most promising solution through re-ranking. Although effective, these methods rely on predetermined pipelines or coordination rules, which limit flexibility and adaptability. In contrast, our method learns hierarchical multi-agent system automatically by jointly optimizing sub-agents and an orchestrator, avoiding manual task decomposition and fixed ensemble strategies.

3 PRELIMINARIES

Software engineering agents We study the problem of using LLMs to resolve real-world GitHub issues, where each issue consists of a textual description and a corresponding code repository. Since issues are not self-contained, solving them requires identifying and modifying relevant parts of the codebase. In this work, we focus exclusively on agentic methods [52], where an LLM interacts with a runtime environment through tool use. Such agents can browse files, execute shell commands, run tests, and edit code directly, giving them the flexibility to tackle long-horizon tasks end-to-end.

Markov Decision Process (MDP) We model agent–environment interaction as a finite-horizon Markov decision process (MDP) [37], $\mathcal{M} = (\mathcal{S}, \mathcal{A}, r, H)$. At each step t, the agent observes a state $s_t \in \mathcal{S}$, consisting of the issue description x and the history of prior tool interactions $h_{t-1} = (a_1, o_1, \ldots, a_{t-1}, o_{t-1})$. The agent samples an action $a_t \in \mathcal{A}$ from its policy $\pi(a_t \mid s_t)$, where $\mathcal{A}$ includes all available tools and commands. Executing a_t yields an observation $o_t \in \mathcal{O}$ (e.g., logs, diffs, or test results), updating the state to s_{t+1}. A trajectory $\tau = (s_0, a_0, \ldots, s_T, y)$ terminates at $T \leq H$ when the agent submits a patch y (forced at $T = H$ if none is submitted earlier). Rewards are sparse:

$$r(s_t, a_t) = 0 \text{ for } t < T, \qquad r(s_T, a_T) = \begin{cases} 1 & \text{if } y \text{ passes all tests,} \\ 0 & \text{otherwise.} \end{cases}$$

The agent's goal is to maximize the expected rewards $J(\pi) = \mathbb{E}_{\tau \sim \pi}[r(s_T, a_T)]$. With sparse rewards and long horizons, discovering successful trajectories is challenging.

Temporal Abstraction via Semi-MDP (SMDP) Semi-Markov Decision Process (SMDP) framework [43] is widely used to mitigate long-horizon sparse reward problems. Instead of issuing primitive actions $a_t \in \mathcal{A}$, the orchestrator selects a temporally extended action (option) $\omega_t \in \Omega$. Each option corresponds to a sub-agent that executes a sequence of actions $(a_t, \ldots, a_{t+m-1})$ until termination, after which control returns at s_{t+m}, where m denotes the duration of an sub-agent. This reduces decision frequency and simplifies planning.

Multi-Armed Bandit (MAB) Multi-armed bandit (MAB) [26] is a special case of an MDP with a single state and no transitions. At each round t, the learner selects an arm $a_t \in \mathcal{A}$, receives a stochastic reward $r_t \in [0, 1]$ drawn from an unknown distribution, and seeks to maximize the cumulative reward $\sum_{t=1}^{B} r_t$ over a fixed interaction budget B. The MAB framework captures decision-making under uncertainty when only a limited number of trials are available.

4 METHOD: BANDIT OPTIMIZATION FOR AGENT DESIGN (BOAD)

Our goal is to automatically discover a set of K sub-agents $\Omega = \{\omega_1, \cdots, \omega_K\}$ and an orchestrator π that maximizes the expected reward of solving issues. A naive approach is to use evolutionary search over (π, Ω):

$$\max_{\pi,\Omega} \mathbb{E}_{x\sim\mathcal{D}_{\text{design}},\tau\sim\pi}\left[r(s_T, a_T)\right], \tag{1}$$

where $\mathcal{D}_{\text{design}}$ is a *design set* consisting of example problems. In this paper, both the sub-agent and the orchestrator agent are parameterized by their prompt. However, this requires generating many full trajectories τ and repeatedly querying the reward function r, which is prohibitively expensive.

Agent design as multi-armed bandit: We formulate the discovery of orchestrators and sub-agents as a multi-armed bandit (MAB) problem [26], where each arm corresponds to a particular sub-agent and at every round t, K sub-agents are chosen. This framing directs more evaluations toward promising designs while continuing to explore new ones, reducing wasted trajectories on poor candidates. Consequently, it makes automatic discovery of multi-agent systems tractable despite the high cost of evaluations in SWE. A detailed formulation is given in Section 4.1. However, this direct approach faces two challenges.

1. The space of possible orchestrators and sub-agent sets is extremely large and initially unknown, making it impractical to enumerate arms in advance.
2. Even if we evaluate a sub-agent along with an orchestrator and the other sub-agents, credit assignment is ambiguous: some sub-agents may succeed only by "free-riding" on others, so the observed reward does not necessarily reflect their individual contribution.

Next, we illustrate how we tackle these challenges in the following sections.

4.1 AGENT DESIGN AS A MULTI-ARMED BANDIT PROBLEM

The space of orchestrator–subagent pairs (π, Ω) is vast and infeasible to enumerate. To make the search tractable, we maintain an archive Γ of candidate sub-agents. Instead of treating each subset of sub-agents Ω as an arm, we treat each sub-agent $\omega \in \Gamma$ as an arm, enabling information sharing across different sub-agents (will be explained below). At each round t, the algorithm selects a subset $\Omega_t \subseteq \Gamma$ by choosing K arms, instantiates an orchestrator π_t for Ω_t, evaluates (π_t, Ω_t) on example problems from a *design* set, and propagates feedback to all participating sub-agents. Because sub-agents appear in multiple subsets, even unsuccessful combinations can provide useful signals. This formulation supports efficient credit assignment, reduces redundant exploration, and progressively refines estimates u_ω for each $\omega \in \Gamma$. Algorithm 1 summarizes the procedure, with further details provided below.

Bootstrapping a sub-agent archive We begin with an initial archive Γ_0 of candidate sub-agents. This archive is generated by prompting an LLM with the template in Appendix A.1.2. However, simply generating sub-agents is insufficient because the orchestrator may not know how to invoke them. We present sub-agents as tools to the orchestrator and adopt the standard tool-calling protocol from SWE-agent [52]. To call a sub-agent, the orchestrator must parse its docstring to understand the functionality and supply the required inputs. For example, an issue-localizer sub-agent requires the issue summary as input; without it, the sub-agent cannot operate. To ensure this, we introduce a warm-up stage that rewrites each generated sub-agent's docstring into a precise specification of its inputs and outputs, enabling the orchestrator to integrate it correctly. Details are provided in Appendix A.1.1.

Sub-agent evaluation At each round t, we select a set of K sub-agents $\Omega_t = \{\omega_1, \ldots, \omega_K\} \subseteq \Gamma_{t-1}$. Given this set, an orchestrator π_t is instantiated by prompting an LLM (see Appendix A.1.3), and the system (π_t, Ω_t) is evaluated on a subset of example problems from a design set. This evaluation yields a performance score $u_\omega \in [0, 1]$ for each sub-agent $\omega \in \Omega_t$. A straightforward choice for u_ω is the success rate of the system on the design set, but as discussed in Section 4.2, this metric is suboptimal and we propose a more effective alternative.

Balancing exploration and exploitation on sub-agent selection After bootstrapping the archive, the next challenge is deciding which sub-agents to evaluate in each round. To balance exploration with exploitation, we adopt the Upper Confidence Bound (UCB) [26] strategy. For each sub-agent $\omega \in \Gamma_{t-1}$, we track its empirical mean $\hat{\mu}_\omega(t)$ of the performance score of u_ω and selection count $n_\omega(t)$ up to round t. The UCB score of a sub-agent ω at round t is defined as

$$\mathrm{UCB}_\omega(t) = \hat{\mu}_\omega(t) + \sqrt{\frac{2 \ln t}{n_\omega(t)}}.$$

The first term favors sub-agents with high observed performance, while the second term gives an optimism bonus to under-sampled sub-agents (i.e., exploration). At each round t, we select the top-K sub-agents based on their UCB scores, ensuring that evaluations increasingly focus on strong candidates while still allocating time to uncertain ones.

Expanding the archive A fixed archive risks stagnation: once UCB identifies a few strong sub-agents, it will repeatedly exploit them, leaving little opportunity to discover new behaviors. To address this, we expand the archive dynamically using a Chinese Restaurant Process (CRP) [3; 48]. At each round t, we prompt the LLM to generate a new sub-agent distinct from those in the current archive Γ_{t-1} (see Appendix A.1.2). The probability of introducing a new sub-agent is

$$\Pr(\text{new at } t) = \frac{\theta}{\theta + |\Gamma_{t-1}|},$$

where $\theta > 0$ is a concentration parameter. This mechanism ensures diversity: when the archive is small, new sub-agents are frequently added; as the archive grows, the probability decreases, shifting the emphasis toward reuse of existing ones. Over time, the expected number of distinct sub-agents after T rounds grows as $O(\theta \log T)$, providing unbounded but controlled expansion. We also run the warmup stage (Appendix A.1.1) to ensure the sub-agent is usable by the orchestrator.

Algorithm 1 Bandit Optimization for Agent Design (BOAD)

Require: budget B, number of sub-agents to select K, concentration θ

Initialize archive $\Gamma_0 \leftarrow$ BOOTSTRAP.
for $t = 1, 2, \ldots, B$ **do**
  With probability $\frac{\theta}{\theta + |\Gamma_{t-1}|}$, create a new sub-agent ω_{new} and set $\Gamma_t \leftarrow \Gamma_{t-1} \cup \{\omega_{\text{new}}\}$; otherwise set $\Gamma_t \leftarrow \Gamma_{t-1}$.
  for each $\omega \in \Gamma_t$ **do**
    if $n_\omega(t-1) = 0$ **then**
      $\mathrm{UCB}_\omega(t) \leftarrow +\infty$ ▷ force initial exploration
    else
      $\mathrm{UCB}_\omega(t) \leftarrow \hat{\mu}_\omega(t-1) + \sqrt{\frac{2 \ln t}{n_\omega(t-1)}}$
    end if
  end for
  Select top-K sub-agents based on UCB scores as a set of sub-agents Ω_t.
  Instantiate orchestrator π_t conditioned on Ω_t.
  Evaluate (π_t, Ω_t) on a subset of training problems; observe performance score $u_\omega \in [0, 1]$ (Sec. 4.2).
  Update $\hat{\mu}_\omega(t)$ and $n_\omega(t)$ for each $\omega \in \Omega_t$.
end for

4.2 Hindsight Credit Assignment

A central challenge in our framework is defining the performance score u_ω of individual sub-agents ω. A simple approach is to set the score of a sub-agent to the success rate of all trajectories that include it:

$$u_\omega = \frac{1}{|\mathcal{T}_\omega^t|} \sum_{\tau \in \mathcal{T}_\omega^t} \mathbb{1}\{\tau \text{ is successful}\},$$

where $\mathcal{T}_\omega^t$ is the set of trajectories at round t in which ω is used by the orchestrator π. However, this suffers from a "free-rider" problem: a sub-agent may appear effective simply because it often co-occurs with strong sub-agents, even if it contributes little itself.

To overcome this, we adopt a hindsight-based credit assignment strategy. The idea is to reward a sub-agent whenever its actions help the orchestrator make progress toward solving the problem, even if the orchestrator ultimately fails. Thus, sub-agents that provide useful intermediate steps are credited, while those that do not are penalized, regardless of the outcomes. Concretely, let $\tau = (a_1, o_1, \ldots, a_T, o_T)$ denote the trajectory of actions and observations produced during problem solving. For each sub-agent ω that appears in τ, we query an LLM judge (Appendix A.1.4) with the trajectory and obtain a binary label $\ell_\omega(\tau) \in \{0, 1\}$, where $\ell_\omega(\tau) = 1$ indicates that the LLM judge deems ω's contribution in the trajectory as helpful. The performance score of sub-agent ω is then defined as the empirical average over all evaluated trajectories:

$$u_\omega = \frac{1}{|\mathcal{T}_\omega^t|} \sum_{\tau \in \mathcal{T}_\omega^t} \ell_\omega(\tau).$$

This hindsight-based score $u_\omega \in [0, 1]$ provides a more reliable estimate of the utility of ω than success rates. By directly linking credit to judged contributions, it avoids free-riding effects.

5 Experiments

Our experiments address the central question: *Can properly designed hierarchical multi-agent systems improve the generalization performance of SWE agents?* We further analyze how the systems discovered by our algorithm differ from human-designed ones and examine the contribution of each design choice to the overall performance gains.

5.1 Setup

Task format and datasets. We evaluate on the SWE-bench benchmarks: SWE-bench Verified (500 instances) [24] and SWE-bench Live (300 instances) [58]. Verified is a curated, frozen set of real GitHub issues, while Live continuously adds newly collected, human-verified issues from active repositories, making it more resistant to data contamination [50] and better suited for testing generalization to out-of-distribution problems. Each instance includes a GitHub issue, a repository-specific container image, and an executable test harness. The agent must interact with the repository (files and, when available, history) and produce a patch that resolves the issue by passing *all* tests (`pass-to-pass` and `fail-to-pass`).

To avoid overfitting and limit design-time compute, we construct a small *design set* by sampling one random issue per repository (12 total) from Verified, ensuring diversity while keeping the set small. The design set is disjoint from all issues in Live. All results in Tables 2 and 3 are reported on Verified and Live (lite) splits. We also report the result of BOAD on Verified (held out) that exclude the 12 issues used in the design set.

Implementation. All experiments use the SWE-agent scaffold with a set of default tools from SWE-agent [52]: `edit_anthropic` (file viewing/editing), `bash` (restricted shell commands), and `submit`. The orchestrator calls sub-agents through the same API, passing information via a *context* parameter; sub-agents return outputs through this channel without access to the orchestrator's history. We use Claude-4 to generate candidate designs (Section 4.1) with temperature 0.0 and evaluate sub-agent helpfulness (Section 4.2). For execution, both orchestrator and sub-agents use Seed-OSS-36B-Instruct with temperature 0.0, unless specificed, a strong instruction-following model that is not heavily tuned on SWE tasks. This choice ensures improvements reflect the benefit of orchestration rather than fine-tuning on SWE-task specific data. Each sub-agent is equipped with prompts discovered by BOAD, defined with docstrings and argument specs, and invoked via XML-based tool calling.

5.2 MAIN RESULTS

Table 1: Success rate on SWE-BENCH VERIFIED and SWE-BENCH LIVE.

Scale	Model	Scaffold	Verified Resolved (%)	Live Resolved (%)
Large	**GPT-4o** [52]	SWE-agent	23.0	10.0
	GPT-4o [51]	Agentless	38.8	11.7
	Claude 3.5 Sonnet [5]	Agentless	50.8	–
	Claude 3.5 Sonnet [5]	OpenHands	53.0	–
	Claude 3.7 Sonnet [4]	SWE-agent	62.4	13.7[1]
	Claude 4.0 Sonnet [6]	SWE-agent	66.8	–
	Claude 4.0 Sonnet [6]	OpenHands	70.4	–
	DeepSeek-R1 [18]	Agentless	49.2	–
	DeepSeek-V3 [15]	Agentless	42.0	13.3
	GLM-4.5-Air [45]	OpenHands	57.6	–
	GLM-4.5-Air [45]	SWE-Agent	–	17.7
	Qwen3-Coder 480B/A35B Instruct [47]	OpenHands	69.6	24.7
Small	**Qwen3-Coder-30B-A3B-Instruct** [47]	SWE-agent	–	17.0
	Qwen3-Coder-30B-A3B-Instruct [47]	OpenHands	51.6	–
	Devstral-Small-2505 [7]	OpenHands	46.8	–
	Seed-OSS-36B-Instruct [46]	SWE-agent (baseline)	49.8	12.3
	Seed-OSS-36B-Instruct [46]	SWE-agent + Manual Subagent	47.4	14.0
	Seed-OSS-36B-Instruct [46]	SWE-agent + **BOAD**	**53.2**[2]	**20.0**

Success Rate Table 1 shows that with Seed-OSS-36B-Instruct, BOAD resolves **20.0%** of issues on LIVE, ranking second on the leaderboard and outperforming larger models in popular scaffolds (e.g., GPT-4o, DeepSeek-V3, GLM-4.5-Air, Claude 3.7 Sonnet). This is a **63%** improvement over the same model with default SWE-agent tools. On VERIFIED, BOAD achieves **53.12%**, surpassing many larger models (e.g., GPT-4o, Claude 3.5 Sonnet OpenHands, DeepSeek-R1, DeepSeek-V3) and setting a new state of the art among smaller models (e.g., Qwen3-Coder-30B-A3B-Instruct, Devstral-Small-2505), with a **13.4%** gain over the default SWE-agent. Interestingly, adding manually designed sub-agents (Appendix A.1.5) from prior work [8; 35; 11] lowers performance, indicating that human-crafted roles can be misaligned with LLM behavior. Overall, these results demonstrate that BOAD automatically discovers orchestrator–sub-agent structures that not only boost in-distribution performance but also generalize more effectively to out-of-distribution tasks.

Token Analysis In addition to success rate, we analyze token usage in BOAD. Hierarchical multi-agent systems introduce communication overhead, since agents must exchange information, but they can also reduce context length: sub-agents focus on specialized sub-tasks while the orchestrator handles high-level coordination without low-level details. Table 2 compares token usage between SWE-agent and BOAD. Total tokens refer to the average sum of input and output tokens per issue, while max input tokens capture the average maximum input length per instance. Surprisingly, the total token count is comparable—and even lower on SWE-bench-live—than in the original SWE-agent. Moreover, BOAD consistently reduces input tokens, confirming that task decomposition shortens context length.

Table 2: **Token usage.** BOAD lowers input token counts, thus shortening the model's input context length.

Metric	Setting	Verified	Live
Total tokens (M)	SWE-agent	0.92	1.49
	SWE-agent + BOAD	0.93 (+0.7%)	1.13 (-23.8%)
Max input tokens	SWE-agent	34.6k	49.0k
	SWE-agent+BOAD	30.5k (-11.6%)	36.7k (-25.0%)

5.3 ABLATION STUDIES AND ANALYSIS

Does prompt optimization explain the gains? One possible explanation for BOAD 's performance improvement is that it simply arises from better prompt optimization of SWE-agent. To test this, we

[1]The SWE-bench-live leaderboard score was 17.7, based on an earlier issue set from April 2025.

[2]53.1 on the SWE-bench-verified set excluding the 12 issues used in the design set.

Table 3: **Ablation studies and analysis.** Each row corresponds to one research question. Results are reported on SWE-bench Live using Seed-OSS-36B-Instruct unless otherwise specified.

Research Question	Configuration	SWE-Bench Live (%)
Does prompt optimization explain the gains?	w/o Sub-agent	16.3
	w Sub-agent	**20.0**
Do more sub-agents improve performance?	Top-5 sub-agents	13.7
	Top-4 sub-agents	16.7
	Top-3 sub-agents	16.3
	Top-2 sub-agents	**20.0**
	Top-1 sub-agent	16.3
Do we need to customize the orchestrator?	w/o customization	16.7
	w customization	**20.0**
Is expanding the sub-agent archive needed?	w/o expansion	17.0
	w expansion	**20.0**
Is hindsight credit assignment necessary?	Top-3 subagents (success rate)	11.3
	Top-3 subagents (helpfulness)	**16.3**
	Top-2 subagents (success rate)	15.3
	Top-2 subagents (helpfulness)	**20.0**
Are discovered sub-agents transferable to other models?	Claude 3.7 Sonnet	13.7
	+ Top-2 sub-agents (helpfulness)	**16.3**

introduce a baseline that optimizes the SWE-agent prompt without adding sub-agents (w/o Sub-agent). We run 10 iterations: in each, a new SWE-agent prompt is generated by prompting Claude-4 with the template shown in A.1.6, evaluated on 12 issues (the same setting as BOAD). The first iteration is initialized without history, and from the second onward, prompt generation is conditioned on the top five prompts from previous rounds, ranked by performance. Results in Table 3 show that prompt optimization alone does not reach the performance of BOAD, indicating that the gains are not solely due to prompt tuning but from the discovery of effective sub-agents and orchestration.

Do more sub-agents improve performance? One might expect performance to improve as more sub-agents are added, since each can specialize. To test this, we vary the number of top-K sub-agents from 1 to 5 based on the helpfulness score (Section 4.2) and evaluate on LIVE. Surprisingly, Table 3 shows that performance peaks with exactly two sub-agents, achieving 60/300 (20.0%). A single sub-agent (49/300) fails to leverage specialization, while larger teams of three (49/300), four (50/300), or five (41/300) reduce performance due to communication and coordination overhead. These results suggest that small, focused teams strike the best balance, outperforming both minimal and overly large teams of sub-agents.

Do we need to customize the orchestrator? We next ask whether gains come solely from sub-agent discovery or if the orchestrator must also adapt to its team. We compare two prompting strategies: (i) a generic prompt encouraging sub-agent calls (Appendix A.1.1), and (ii) a customized prompt generated by Claude-4 that explicitly references the top two sub-agents (selected by helpfulness scores) and outlines a plan for using them. Both settings use the same sub-agent set, but only the customized prompt allows the orchestrator to reason about and plan calls to specific sub-agents. Results in Table 3 show the customized orchestrator (w customization) achieves 60/300 (20.0%), versus 50/300 (16.7%) (w/o customization) for the generic one. This indicates that while sub-agents provide new capabilities, the orchestrator must also be specialized to effectively coordinate them.

Is expanding the sub-agent archive needed? As discussed in Section 4.1, the initial archive may be limited, and adding new sub-agents during the design process could be necessary to discover stronger ones. To test this, we compare orchestrator performance using (i) sub-agents from the initial archive (w/o expansion) and (ii) sub-agents selected at the end of the design process (w expansion). Both settings use two sub-agents, consistent with our best configuration in Section 5.2, and the orchestrator is generated as described in Section 4.1. Results in Table 3 show that final sub-agents outperform those from the initial archive, highlighting the importance of expanding the archive over time.

Is hindsight credit assignment necessary? To address free-riding issues in sub-agent selection (Section 4.1), we use a helpfulness score to measure each sub-agent's contribution. To test its importance, we compare orchestrator performance when sub-agents are selected by (i) individual success rate versus (ii) helpfulness score. As shown in Table 3, helpfulness-based selection consistently outperforms success-rate selection, indicating that hindsight credit assignment (Section 4.2) is essential for identifying useful sub-agents.

Are discovered sub-agents transferable to other models? Since BOAD optimizes sub-agents for a specific model, we ask whether the best sub-agents differ across models and whether effective sub-agents can transfer. To test this, we apply the sub-agents from Section 5.2 to SWE-agent+Claude-3.7-Sonnet. As shown in Table 3, the discovered sub-agents do transfer to some extent, though the gains are smaller than those achieved with Seed-OSS-36B-Instruct, the model used for sub-agent optimization.

5.4 Qualitative Analysis of Single- vs Multi-Agent Outcomes

We manually inspected trajectories in which the single- and multi-agent systems produced different outcomes. Three recurring patterns emerged:

1. **Over-editing (multi-agent advantage).** Single agents frequently produced extremely long patches, including attempts to create new tests and edits outside the scope of the bug. Such patches inflate apply time and increase the chance of failing `pass-to-pass`, even if the agent is able to address the primary fault. In contrast, the multi-agent system tended to emit short, localized patches, highlighting the advantage of separating phases like localization and editing/testing.
2. **Multi-site fixes and coverage (multi-agent advantage).** When the fix required edits at multiple call sites or modules, the single agent often either over-edited unrelated regions or missed one or more necessary locations. The hierarchical system mitigated both omission and extraneous edits by delegating to a sub-agent for localization, which did a thorough analysis of the repository before making any targetted modifications.
3. **Error propagation from unvalidated sub-agent outputs (multi-agent failure mode).** In a minority of cases, the multi-agent system failed while the single agent succeeded. Inspecting these outputs, we found that erroneous sub-agent outputs (e.g., incomplete span identification, misinterpretation of the issue) were accepted as ground truth by the orchestrator, leading subsequent steps astray. Because there is no intermediate validation or self-checking, the orchestrator has limited ability to recover from such upstream.

These observations align with our hypothesis: hierarchical delegation constrains edit scope and improves coverage of multi-site fixes, but introduces a new dependency on the *quality of sub-agent handoffs*. Incorporating lightweight verification (e.g., span cross-checks, invariant tests, or dual-read localization) is a promising mitigation for the third failure mode.

6 Discussion & Conclusion

We present BOAD, a framework that formulates hierarchical multi-agent design as a sequential, online decision making problem to automatically discover multi-agent systems for long-horizon software engineering tasks. Our experiments show that automatically discovered sub-agents, when combined with a customized orchestrator, outperform single-agent and manually designed multi-agent systems on both SWE-Bench Verified and SWE-Bench Live.

Limitations and Future Work: We find that discovered sub-agents transfer across models only partially and failure cases highlight error propagation when orchestrators unconditionally accept sub-agent outputs. Future work should explore evolution on large models, adaptive team sizing, verification, as well as extending the framework to domains beyond software engineering.

Ethics Statement

Coding agents hold strong promise for automating code generation and bug fixing, but they also carry risks of unintended or harmful outputs. For instance, an LLM-based agent may produce

commands that could compromise a system (e.g., downloading unauthorized packages or deleting user files with `rm -rf`). To mitigate these risks in our study, all experiments were conducted within Docker containers, providing isolated and sandboxed environments that prevent harmful commands from impacting real user devices and substantially reducing the potential for actual harm. Our implementation also builds upon the SWE-Agent framework, which has been previously published and reviewed under established ethical standards. We carefully follow its curated protocols and licensing requirements.

Nevertheless, as with any AI-based coding agent framework, there remains the risk of deliberate misuse, for example, a malicious user prompting the system to generate harmful or hacking code. While our contribution is centered on advancing the technical design of hierarchical coding agents, we emphasize that real-world deployment should be coupled with responsible auditing and oversight, so that potential misuse and unintended consequences can be effectively mitigated.

Reproducibility Statement

For all open-source LLMs (e.g., Seed-OSS-36B-Instruct, Qwen3-Coder-30B-A3B-Instruct), we rely on their official releases. Commercial LLMs and LLM-based tools are accessed through their official APIs and reference implementations. We provide detailed implementation notes of BOAD, including the prompt design for meta-agents, sub-agents, and LLM judges, in Section 5.1. To further support reproducibility and foster future research, we will also release all of our code, used data, and prompts.

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A IMPLEMENTATION DETAILS

A.1 PROMPT TEMPLATES

A.1.1 PROMPT TEMPLATE FOR REFINING SUBAGENT DURING WARMUP STAGE

Prompt template for refining subagent during warmup stage

```
You are improving a subagent's prompts/config for a software engineering (SWE) automation system, based
↪  on recent run trajectories. The subagent is used by an AI main agent to address code issues.

CONTEXT
- You will receive trajectory summaries below, starting with the main agent's trajectory, followed by
↪  any subagent trajectories in call order.
- Each summary shows what the agent did, what was observed, and how far it progressed.

GOAL
Analyze the subagent's performance and suggest improvements to make it:
1. More discoverable by the main agent (when appropriate)
2. More reliable in its behavior
3. More useful in its output

ANALYSIS FRAMEWORK
Consider these questions:
- Did the main agent discover and use the subagent when it should have?
- Did the subagent behave as expected and return useful information?
- Were there missed opportunities or inefficient behaviors?

IMPROVEMENT TYPES
Focus on one or more of these areas:
1. **docstring**: Make the subagent easier for the main agent to discover and choose appropriately.
↪  CRITICAL: Make sure to include "[subagent]" at the beginning of the docstring.
2. **context_description**: Improve the description of the 'context' argument (the only argument) to be
↪  clearer and more helpful
3. **instance_template**: Better incorporation of context, clearer framing for each problem instance

Note that the docstring and context_description are visible only to the main agent, while the
↪  instance_template is visible only to the subagent.
Thus, if the subagent was not called, you should not edit instance_template. Similarly, if the only
↪  issue is the subagent's trajectory, not how it was called, do not edit docstring or
↪  context_description.

PRINCIPLES
- Make surgical, targeted improvements rather than broad rewrites
- Preserve existing style and capabilities. Only edit components that need improvement.
- Focus on clarity, discoverability, and reliability
- Ensure generality. Avoid repo- or issue-specific assumptions.
- CRITICAL: DO NOT WRITE ANYTHING SPECIFIC TO THE PARTICULAR CODEBASE, PROJECT, OR DOMAIN.

OUTPUT FORMAT
First, explain your reasoning about what issues you noticed with the provided trajectory and what
↪  improvements you're making. Then, output the YAML in a code block.
**IMPORTANT**: Only suggest edits when you identify a clear, specific problem. If the entire subagent
↪  is working well, use an empty updates dictionary.

Sample outputs:
**When improvements are needed:**
Explain your reasoning here.
```yaml
updates:
  docstring: "<improved docstring if needed>"
  context_description: "<improved context argument description if needed>"
  instance_template: "<improved instance template if needed>"
```

RULES
- Only include keys that you intend to change.
- Start with `updates:` as the top-level key. If there are no updates to make, the value for `updates`
↪ should be an empty dictionary.
- You may update any combination of the three fields (docstring, context_description,
↪ instance_template), but only include a field if it needs improvement.
- No explanations or extra content in the YAML
- Keep each field concise but complete

HEURISTICS
- **Discovery issues**: Strengthen docstring with clear use cases and when to invoke
- **Insufficient context passed to subagent**: Improve context_description with clearer argument
↪ explanation
- **Subagent behavior and output (Incorrect subagent trajectory or return information)**: Improve
↪ instance_template with better instructions and output specifications

{{TRAJECTORIES}}
```

A.1.2 META AGENT PROMPTS

Prompt for generating a new subagent configuration

```
You are an expert at designing custom tools for SWE-agent, an autonomous agent that can resolve code
↪  issues in large repositories.

YOUR TASK
Invent a subagent tool for SWE-agent.
- The subagent should enable the main agent to better perform its task of automatically resolving code
↪  issues in large static repositories.
- Design for broad applicability across the full workflow. Create broad subagents that are can solve an
↪  entire step of the pipeline, such as:
  - code localization
  - reproducing issues and running scripts/tests
  - code editing/patching
  - code testing
- The subagents created should ONLY be focused on correctness of the final patch (e.g. style,
↪  complexity of code does not matter)
- PRIORITIZE TOKEN EFFICIENCY: Design concise, focused subagents that use minimal tokens. Avoid verbose
↪  explanations or redundant information that wastes tokens.
- If you see a subagent that looks good but has bad token efficieny, you may generate a similar
↪  subagent with the same function but better implementation.
- The subagent takes a SINGLE argument that is a string, called "context".
- BE NOVEL! Think carefully about how to help the main agent perform one of its subtasks.
  - Example subagents include localize, patch_editor, or code_tester.
- Do not create a subagent that overlaps with previous subagents (other than the token efficiency
↪  situation).
- In your reasoning, you must explicitly list which steps the subagent supports (examples: explore,
↪  read/search, edit, run, validate) and the expected outputs for each supported step.
- CRITICAL: Your output should be PLAIN TEXT in valid YAML format (not inside a YAML block), so that it
↪  can be directly parsed by pyYAML.
  - CRITICAL: Output exactly ONE YAML document with the tool under a single key, which is the name of
  ↪  the tool.
  - The name of the tool should be simple and descriptive.
  - The docstring for each tool should be comprehensive and describe what the output contains, as well
  ↪  as the state of the repository after the subagent is finished (if files will be edited or not,
  ↪  etc.).

The structure must be exactly as follows:
Add reasoning here about WHY you design this subgaent...
```yaml
tool_name:
  signature: "tool_name <context>"
  docstring: docstring: "comprehensive description of this subagent, the output, and the state of
  ↪  repository on completion. Starts with '[subagent]:"
  arguments:
    - name: context
      type: string
      description: "detailed description of what the context parameter should contain"
      required: true
  subagent: true
```

Sample output:
To address step 3, it may be useful to have a patch editor subagent. This would go well with previosu
↪ subagents and help the main agent more efficiently patch the issue.
```yaml
patch_editor:
  signature: "patch_editor <context>"
  docstring: "[subagent] Fixes a specific part of code that has errors. Outputs the changes made with
  ↪  reasoning. After calling, the correct changes are already implemented in the repository."
  arguments:
    - name: context
      type: string
      description: "A string containing the specific file path to make edits in, the lines where edits
      ↪  need to be made, a comprehensive description of the issue with the code (do not assume the
      ↪  subagent has any information about the repository or problem statement), and what to edit."
      required: true
  subagent: true
```
{{PREVIOUS_ITERATION_FEEBACK}}
```

Prompt for generating subagent templates

```
You are an expert at creating SWE-agent subagent configuration files for automating code-patching tasks
↪  in large GitHub repositories.
Given a description of the subagent, you need to generate the system_template and instance_template
↪  parts that will be used in the subagent configuration.

IMPORTANT FORMATTING RULES:
- First output your reasoning that details your thinking process for creating the templates. Then,
↪  output a yaml block with both templates.
- Use MINIMAL spacing - avoid excessive blank lines
- Use only SINGLE blank lines between sections (never double or triple spacing)
- Keep templates compact and readable without unnecessary whitespace
```

```
- CRITICAL: Use YAML literal block syntax with | and |- (see example below)
- Do NOT use quoted strings - use literal blocks to avoid quotes in output
- Replace ONLY text in [] with text specific to the subagent. Do NOT MODIFY any other parts.
- Copy EXACTLY the parts other than [], including how to call the functions (e.g.
↪  "<function=example_function_here>")

Output format:
[Reasoning here...]
```yaml
system_template: |
  You are a helpful [role] assistant that can interact with a computer to [main task].
  <IMPORTANT>
  * If user provides a path, you should NOT assume it's relative to the current working directory.
  ↪  Instead, you should explore the file system to find the file before working on it.
  </IMPORTANT>

  You have access to the following functions:
  {{command_docs}}

  If you choose to call a function, you must ONLY reply in the following format with NO suffix:
  Provide any reasoning for the function call here.
  <function=example_function_name>
  <parameter=example_parameter_1>value_1</parameter>
  <parameter=example_parameter_2>
  This is the value for the second parameter
  that can span
  multiple lines
  </parameter>
  </function>
  (You must use the exact text function=" and "parameter=" for each function and argument, respectively,
  ↪  e.g. <parameter=command>value</parameter>)

  <IMPORTANT>
  Reminder:
  - Function calls MUST follow the specified format, start with <function= and end with </function>
  - Required parameters MUST be specified
  - CRITICAL: Only call ONE function at a time
  - Always provide reasoning for your function call in natural language BEFORE the function call (not
  ↪  after)
  </IMPORTANT>

  <pr_description>
  {{problem_statement}}
  </pr_description>

  CRITICAL: Use the submit_subagent function to provide the results when you are finished with your
  ↪  task.
  You are ONLY responsible for your specific assigned task. Do NOT attempt to resolve entire
  ↪  pr_description, only your task.
  Your goal is to complete your task in the MINIMAL NUMBER of steps. Resolve the issue fast and call
  ↪  submit_subagent as soon as possible.

instance_template: |-

  Your task:
  [Provide detailed, step-by-step instructions for your assigned subagent task, tailored to your
  ↪  specific role. The instructions must ONLY reference this subagent's function.]
  [If a context argument is provided, you MUST include its contents by inserting "{{context}}" here and
  ↪  explaining what the parameter is.]

  **CRITICAL: STAY IN YOUR LANE**
  - You are ONLY responsible for your specific assigned task
  - You are NOT responsible for solving the entire issue
  - You are NOT responsible for other subagent tasks
  - Focus EXCLUSIVELY on your assigned task and nothing else
  - CRITICAL: Call EXACTLY one function in your output!
  - CRITICAL: When you are finished, immediately call submit_subagent. Do not call any other tools or
  ↪  produce additional output.

  Focus exclusively on your assigned task and strictly follow these instructions. Do not attempt to
  ↪  address unrelated parts of the PR or perform work outside your specific subagent role.
  Use the submit_subagent tool after you are finished with your specific task to provide a clear and
  ↪  complete summary of your findings or changes.
  Your thinking should be thorough and so it's fine if it's very long.
```

Rules for generating templates:
1. The system_template should clearly define the subagent's role and capabilities based on the
↪ available tools
2. The instance_template should provide clear instructions for each task
3. Both templates should maintain consistent formatting with the base template
4. Ensure the templates encourage thorough analysis and clear documentation
5. MUST use literal block syntax: system_template: | and instance_template: |-
6. Never use quoted strings for templates
7. You should copy the given system template exactly other than the first sentence.
8. Modify the system template in the spots with [].

{{PREVIOUS_ITERATION_FEEDBACK}}
```

A.1.3 CUSTOM ORCHESTRATOR PLAN PROMPT

Prompt template for generating a custom orchestrator plan given a set of subagents

```
You are a master workflow architect for automated software engineering. Your job is to design
↪  innovative, strategic workflows that maximize the effectiveness of available tools.

CONTEXT: You're designing workflows for an AI assistant that solves coding problems in software
↪  repositories. The assistant receives a problem description (like a bug report, feature request, or
↪  code issue) and needs to systematically work through the codebase to understand, fix, and validate
↪  the solution. The assistant has access to specialized "subagents" - each designed for specific
↪  aspects of the coding workflow.

You will be given a toolkit of specialized "subagents" - each with unique capabilities. Your challenge
↪  is to:
1. **Design** a comprehensive problem-solving plan that addresses the coding issue systematically
2. **Integrate** subagents strategically where they add the most value to your workflow
3. **Optimize** the sequence and wording of the plan to minimize the number of steps that the AI
↪  assistant takes while remaining effective

Think like a senior engineer designing a solution strategy. Consider:
- What are the key phases needed to solve this type of coding problem?
- Which subagents would be most valuable for specific phases?
- How can you combine subagent work with direct problem-solving phases?
- What's the most logical progression to integrate subagent input and output to solve the issue?
- How can you utilize subagents to minimize language model token usage and number of steps?

INPUT
- The available subagents will be provided inline between the following tags:

  <available_subagents>
  {{subagents_overview}}
  </available_subagents>

  The content in <available_subagents> lists each subagent with its name and short docs
  ↪  (summary/description). Treat it as the authoritative source for tool names and purposes.

WHAT TO OUTPUT
- Output ONLY your strategic plan as plain text (no YAML, no code fences, no headers).
- Each phase MUST start with a number and a period, e.g. "1. ...".
- For subagent phases, use the exact form: "Use the <name> subagent to ..."
- For direct phases, describe the action clearly without mentioning subagents, ensuring that it can be
↪  applied to any problem.
- Be creative and strategic - design workflows that combine different approaches effectively
- Keep 3 to 7 steps total, but make each step purposeful and well-reasoned
- Make sure the last steps are:
  - After you have solved the issue, delete any test files or temporary files you created.
  - Use the submit tool to submit the changes to the repository.
- Do not mention any function-call formats or system details

EXAMPLE (illustrative only; adapt to the given input)
<available_subagents>
- name: issue_localizer | Identify files and code regions relevant to the issue.
- name: error_reproducer | Reproduce the failing behavior and capture commands/outputs.
- name: code_tester | Run tests/commands to verify the fix and regressions.
</available_subagents>

Expected output EXAMPLE (plain text only):
1. Use the issue_localizer subagent to map the problem space and identify all potentially affected
↪  files and code regions.
2. Analyze the problem description and examine the identified files to understand the root cause and
↪  requirements.
3. Use the error_reproducer subagent to create a reproducible test case and capture the exact failure
↪  conditions.
4. Design and implement the fix based on the analysis, focusing on the specific files and code areas
↪  identified.
5. Use the code_tester subagent to validate the fix against the original failure case and run
↪  regression tests.
6. After you have solved the issue, delete any test files or temporary files you created.
7. Use the submit tool to submit the changes to the repository.

Now, based on the provided subagents, produce ONLY the numbered plan as plain text:
```

A.1.4 PROMPT TEMPLATE FOR CHECKING IF A SUBAGENT WAS HELPFUL IN A GIVEN INSTANCE

Prompt template for checking if a subagent was helpful in a given instance

```
CONTEXT:
These trajectories show a software engineering agent trying to fix a bug or implement a
↪  feature. The agent can use various tools including subagents (specialized AI
↪  assistants) to help solve the problem.
```

```
TRAJECTORIES:
{{TRAJECTORIES}}

TOOL TO ANALYZE: {{TOOL_NAME}}

Your task is to determine if the subagent "{{TOOL_NAME}}" was helpful in this set of
↪  trajectories.
A tool is considered helpful if:
1. It was called/invoked by the main agent in the main agent trajectory
2. It provided useful information, analysis, or insights that contributed to solving the
↪  problem
3. The main agent made progress after using this tool (e.g., identified the issue, made
↪  code changes, validated results, etc.)
4. It completed its task as intended (followed proper analysis process, not just got
↪  lucky results)

Look for positive evidence such as:
- The subagent being called with appropriate parameters
- The subagent providing insights that led to code changes or problem understanding
- The main agent referencing or building upon the subagent's output
- The subagent's output being used in subsequent reasoning or actions

Look for negative evidence such as:
- The subagent not being called by the main agent, or called incorrectly
- The subagent providing irrelevant or incorrect information that was not later used
- The subagent's response was valid but did not move the main agent closer to resolving
↪  the problem.
- The subagent failed to execute properly or had many errors during the its run.
- The subagent's output appeared correct, but its trajectory did not actually achieve
↪  those results (e.g., claimed to test code but just reported all tests passed).
- The main agent had to call the subagent over and over again to get the proper results.
- The subagent trajectory was unnecessarily long or verbose, taking many steps to
↪  complete its task
- The main agent trajectory became inefficient due to excessive subagent calls or overly
↪  verbose subagent responses
- The subagent's results did not actually help the main agent make progress in resolve
↪  the issue. If a subagent did not contribute to producing the correct patch, e.g. only
↪  improved performance, style, or documentation, this is NOT helpful.

Respond with YAML format (exactly):
```yaml
helpful: true/false
reasoning: |
  Brief explanation of why the tool was or wasn't helpful, including specific evidence
  ↪  from the trajectories
```

- Always use the block scalar `|` for `reasoning` and indent its text by two spaces.
- Only respond with the YAML block; no additional text before or after.
```

A.1.5 MANUALLY DESIGNED SUBAGENT CONFIGURATIONS

issue_localizer configuration

```
\textbf{docstring}: A subagent that localizes the issue in the repository. Takes a context string
↪  specifying the brief description of the issue. Outputs a brief report about which files and lines
↪  are relevant to the issue.
\textbf{argument}: context (string) [required] { A string containing the brief description of the
↪  issue.
\textbf{instance template}:
Issue description:
{{context}}

Please identify which files and specific lines or functions are most relevant to this issue. Output a
↪  short, clear report that mentions:

- File paths
- Line numbers or function names
- A one-sentence explanation for why each location is relevant

Keep the report concise and focused on helping later agents work on the correct parts of the
↪  repository.
```

error_reproducer configuration

```
\textbf{docstring}: A subagent that creates and executes test scripts to verify reported errors.
↪  Outputs the result of the tests and locations of test files created.
\textbf{argument}: context (string) [required] { A string containing error details, file paths and line
↪  numbers of code relevant to the error, and expected vs actual behavior.
\textbf{instance template}:
Error context:
{{context}}

Please create and execute a temporary reproduction script to verify this error. You should:
- Create temporary files (prefixed with 'tmp_')
- Include only what's needed to reproduce the error
- Report whether the error reproduces exactly as described
- Note any deviations from expected behavior

Output a short, clear report that mentions:
- Result of the tests
- Locations of test files created
```

code_editor configuration

```
\textbf{docstring}: A subagent that implements specified code changes in the repository. Outputs the
↪  specific code changes made, file paths/line numbers edited, and what should be tested to verify the
↪  fix.
\textbf{argument}: context (string) [required] { A string containing the code snippet(s) to modify and
↪  file path(s), and the changes to be applied.
\textbf{instance template}:
Context for code changes:
{{context}}

Please implement the specified code changes in the repository. You should:

- Identify the relevant files and code sections
- Make precise edits according to the specification
- Maintain code quality and consistency
- Output a short, clear report that mentions:
- File paths/line numbers edited
- What should be tested to verify the fix
```

code_tester configuration

```
\textbf{docstring}: A subagent that tests code after edits have been made to verify the fix works
↪  correctly. Outputs the result of the tests.
\textbf{argument}: context (string) [required] { A string containing the specific code changes made,
↪  file paths, and original error.
\textbf{instance template}:
Code changes made:
{{context}}

Please test the code after the edits to verify the fix works correctly. You should:

Use existing test files if available (prefixed with 'tmp_'), or create new ones as needed

- Test the specific functionality that was changed
- Determine whether or not the original error is fixed.
- Output a short, clear report that mentions:
- List of tests run and results of the tests
- Whether the original error is fixed, and if any new errors were introduced
```

A.1.6 PROMPT TEMPLATE FOR GENERATE PROMPT FOR ORCHESTRATOR UNDER ORCHESTRATOR ONLY SETINGS

Prompt Template for generate prompt for orchestrator under orchestrator only setings

```
You are a master workflow architect for automated software engineering. Your job is to design effective
↪  workflows that solve coding problems efficiently.

CONTEXT: You're designing workflows for an AI assistant that solves coding problems in software
↪  repositories. The assistant receives a problem description (like a bug report, feature request, or
↪  code issue) and needs to work through the codebase to understand, implement changes, and validate
↪  the solution.

Your goal is to create workflows that are both effective at solving problems and efficient in their
↪  execution. Focus on designing strategic approaches that lead to successful problem resolution.

CONTEXT FOR PLAN USAGE:
Your generated plan will be inserted into this agent template context:
```

```
```
I've uploaded a python code repository in the directory {{working_dir}}. Consider the following PR
↪ description:

<pr_description>
{{problem_statement}}
</pr_description>

Can you help me implement the necessary changes to the repository so that the requirements specified in
↪ the <pr_description> are met? I've already taken care of all changes to any of the test files
↪ described in the <pr_description>. This means you DON'T have to modify the testing logic or any of
↪ the tests in any way! Your task is to make the minimal changes to non-test files in the
↪ {{working_dir}} directory to ensure the <pr_description> is satisfied. When solving the task,
↪ **first create a plan by breaking the problem into subtasks**. Think systematically about the steps
↪ needed to understand the problem, locate relevant code, implement changes, and verify the solution.
↪ Follow this process:

{{plan}} <-- YOUR PLAN GOES HERE

You MUST follow the plan exactly.
```

AVAILABLE TOOLS:
- bash: Execute shell commands for searching, testing, running scripts, exploring codebase structure
- str_replace_editor: View, create, and edit files with precise string replacement capabilities
- submit: Submit the final solution

LEARNING FROM HISTORY:
<sampled_templates>
{{sampled_templates_summary}}
</sampled_templates>

If historical templates are provided above, identify what made the highest-scoring approaches
↪  successful and what caused failures. Look for patterns in tool usage, step efficiency, and
↪  problem-solving strategies. If no history exists, design breakthrough approaches that challenge
↪  conventional software engineering workflows.

WHAT TO OUTPUT:
- Create a step-by-step plan that an AI agent can execute systematically
- Each step must clearly specify tool usage ("Use bash to..." or "Use str_replace_editor to...") and
↪  expected outcomes
- Design for Python repositories and PR-based problem solving
- Focus on minimal, targeted changes rather than broad exploration
- Structure as numbered steps (1., 2., 3., etc.) with logical flow
- Final step must use submit tool to deliver the solution
- Make each step actionable and specific enough for precise execution
- Output ONLY the numbered plan as plain text (no formatting, headers, or explanations)
```

B THE USAGE OF LARGE LANGUAGE MODELS (LLMS)

In our work, we used large language models (LLMs) for two purposes: (1) as a general writing assistant to check the grammar of the manuscript for readability, and (2) as the model component of our proposed system BOAD, where LLMs function as the evolution engine, meta-/sub-agents, and evaluation judges in experiments with mainstream coding agents. All research ideas, methodological contributions, and conclusions are solely those of the authors, who take full responsibility for the content of this work.