Test-Time Learning with an Evolving Library

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Abstract

We introduce EVOLIB, a test-time learning framework that enables large language models to accumulate, reuse, and evolve knowledge across problem instances without parameter updates or external supervision. Instead of adapting model parameters, our approach maintains a shared library of *knowledge abstractions*, including modular skills and reflective insights, automatically extracted from the model's own inference trajectories. To support continual improvement, we introduce a principled weighting and consolidation mechanism that jointly optimizes for immediate utility and long-term value. This allows simple, instance-specific abstractions to evolve into more general and reusable ones over time. Across challenging benchmarks in mathematical reasoning, code generation, and multi-turn agentic environments, EVOLIB improves substantially over the top test-time scaling and learning methods without ground-truth feedback.[1]

1 Introduction

Humans can learn from past experience and encode that knowledge in abstract, reusable, and extensible forms. This allows them to accumulate and refine knowledge over time, enabling adaptation to novel situations with far less repeated effort. By contrast, large language models (LLMs) typically handle each input problem independently [1–6] or share memory across problem instances by storing and retrieving past problems and trajectories from a global memory [7–9], which hinders LLMs from inducing generalized knowledge or skills across problems.

Test-time learning (TTL) bridges this gap by enabling models to adapt during inference, which improves performance across a sequence of tasks [10–12]. In principle, TTL allows models to correct systematic errors, discover reusable strategies, and build knowledge across problems. However, existing approaches face two fundamental limitations in the context of modern LLMs. First, most methods rely on gradient updates on model parameters to learn effectively from test-time signals. These approaches are not applicable in the increasingly common *black-box* setting, where model weights are inaccessible. Second, many TTL approaches depend on external supervision signals, such as reward functions or example test cases, to guide learning. Such signals are unavailable in many real-world application scenarios.

A complementary line of work, *test-time scaling*, improves performance for black-box LLMs without external supervision, by allocating more computation per instance (e.g. through sampling [1], searching [6], or iterative refinement [4]). While effective, these methods treat each problem in

[1]Code is available at: https://github.com/microsoft/EvoLib.

isolation: the knowledge uncovered during the search process is discarded after inference, preventing the model from inducing generalizable knowledge across problems.

In this paper, we introduce EVOLIB, an evolving library for test-time learning that overcomes these limitations by enabling *knowledge accumulation without parameter updates or external supervision*. The key idea is to maintain a structured, evolving collection of *knowledge abstractions*. The system extracts two types of abstractions from model-generated solutions: (1) *modular skills*, which capture reusable procedures, and (2) *reflective insights*, which encode common errors and corrective strategies.

EVOLIB is governed by two central principles:

- **Abstraction:** Instead of memorizing raw experiences, the library distills them into reusable knowledge units that can be flexibly recomposed across tasks. This enables more efficient transfer compared to memory-based approaches that store unstructured trajectories.
- **Evolution:** The library is continuously updated through iterative abstraction extraction, consolidation and dynamic weight computation. We introduce a novel credit assignment mechanism based on *Information Gain* (IG) and *Future Information Gain* (Future IG), which jointly capture the immediate usefulness of an abstraction and its potential for generating valuable future abstractions. This mechanism promotes the emergence of increasingly useful and extensible abstractions over time.

Importantly, the entire process is *self-supervised* – the model evaluates its own generated solutions and extracts abstractions without relying on external ground-truth signals. This makes the approach applicable to highly challenging tasks and deployment scenarios where external feedback is unavailable or expensive to collect.

We evaluate EVOLIB on a diverse suite of benchmarks spanning mathematical reasoning, code generation, and multi-turn agentic tasks. Across all settings, our method demonstrates consistent improvements over the top test-time scaling and learning approaches with more efficient token usage. Further results in the continual learning setting support that EVOLIB enables continual learning that is less dependent on task ordering, whereas existing TTL methods based on linear knowledge updates are more sensitive to the ordering.

2 Related Work

Test-time scaling and adaptation. There is a growing body of work that improves LLM performance by allocating additional computation at inference time rather than updating model parameters. Representative approaches include best-of-N sampling and self-consistency [1], self-verification with and without feedback [2–4], iterative refinement and aggregation [5, 6]. While effective, these methods treat each problem independently: any knowledge discovered during inference is discarded after solving a single instance. By contrast, EVOLIB explicitly retains and reuses knowledge across problems, enabling continual improvement over a stream of tasks.

More closely related are *test-time learning* and *test-time training* methods that adapt model behavior at test time. Recent work formulates test-time learning for LLMs as self-supervised optimization on unlabeled test data [10] or few-shot learning on example test cases [11], often using lightweight parameter updates [13, 14]. These methods require gradient updates on model parameters, whereas EVOLIB performs test-time learning purely through abstraction induction and evolution, without any parameter modification.

Memory-augmented LLMs. Several recent works augment LLMs with external memory to persist information across queries or interactions. Retrieval-augmented generation and dynamic prompt construction store and retrieve raw past experience [7, 8]. [9] introduces ExpRAG, a simple framework for retrieving and reusing prior experience, along with a variant that allows the agent to iteratively refine the retrieved memory. While these approaches demonstrate the importance of shared memory across queries, they primarily store unstructured trajectories or episodic experiences. EVOLIB differs by distilling experience into *extensible abstractions* and by explicitly promoting extension and consolidation to produce more general knowledge units.

Skill and knowledge discovery. The idea of learning reusable skills from experience has a long history in program synthesis and cognitive science [15–17]. One line of work learns how to use

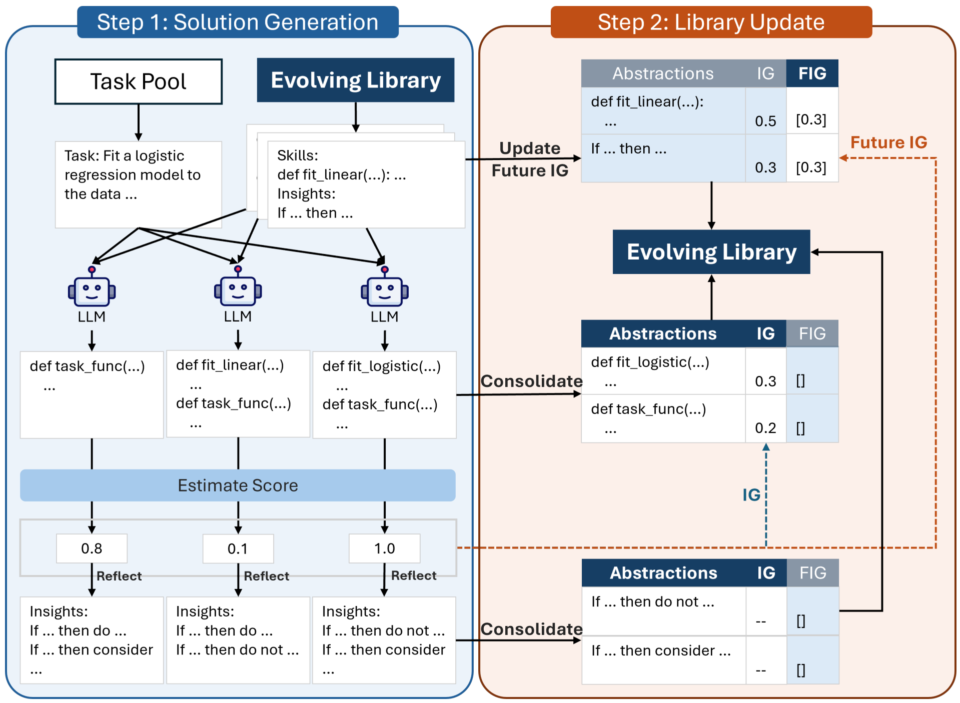


Figure 1: Overview of the EvoLib algorithm. EvoLib performs test-time learning by repeatedly: (i) solving tasks using sampled abstractions, (ii) extracting new abstractions, consolidating them into the library, and propagating credit to both new and previously used abstractions via Information Gain (IG) and Future IG.

existing tools effectively [18, 19]. Another line of work focuses on extracting reusable skills, such as subroutines or functions, from solved programs or successful trajectories [20–24], or inducing reflective insights from model-generated programs or trajectories together with feedback [25–29]. Furthermore, inspired by the recent development of agentic "autoresearch" loops [30–32], recent works propose skill evolution by iteratively refining a skill set based on new trajectories [33, 34]. Most existing approaches learn such libraries on training tasks where external success signals are available, whereas our approach can be applied solely at test-time.

Closest to our setting, AWM [35] proposes to maintain a memory of reusable routines extracted from action trajectories with optional external feedback, while Dynamic Cheatsheet [36] induces high-level principles and procedural knowledge via self-reflection. Similarly, a concurrent work constructs a memory of reasoning strategies distilled from self-judged successful and failed experiences [37]. However, these approaches either treat memory as a monolithic artifact that is refined holistically [36] or append new items into the memory in a linear fashion [35, 37], making them susceptible to three major failure modes: *misgrouping*, where experiences from different types of tasks are consolidated into the same abstraction; *interference*, where repeated LLM rewriting strips away applicability conditions and turns useful lessons into overly broad guidance; and *overfit*, where memory becomes tied to narrow surface patterns rather than reusable strategies [38]. EvoLib addresses these issues by introducing a principled weighting, sampling, and consolidation mechanism that drives the emergence and nonlinear evolution of abstractions, guided by immediate and long-term utility across instances (see the extended results in Section B).

3 EvoLib

EvoLib is characterized by two key properties. First, **abstraction** – the library stores generalizable knowledge distilled from raw trajectories, making it easier for LLMs to adapt and reuse past experience across problems compared to memory-based methods that store raw trajectories. Second, **evolution** – the library is continuously updated through a consolidation mechanism and a dynamic weighting scheme based on Information Gain and Future Information Gain, enabling abstractions to improve over time.

3.1 Problem Formulation

We represent an agent augmented with EvoLib as a tuple $(\Phi, \mathcal{K})$, where Φ is the base LLM and $\mathcal{K}$ is the library. Starting with an empty library $\mathcal{K}_0 = \emptyset$, the agent is given a sequence of tasks $\{x_1, x_2, ..., x_T\}$, each sampled from the task pool $\mathcal{T}$, and the library $\mathcal{K}_t$ evolves with the history. At step t, given the input problem x_t and the current library $\mathcal{K}_{t-1}$, the agent samples abstractions from the library and generates a solution $\tilde{y}_t$ for x_t:

$$\{z_{t-1}\} \sim \mathrm{Sample}(\mathcal{K}_{t-1}, x_t),$$
$$\tilde{y}_t \sim P_\Phi(\cdot \mid x_t, \{z_{t-1}\}),$$

then extracts new abstractions $\{z_t\}$ from $\tilde{y}_t$:

$$\{z_t\} = \mathrm{Extract(x_t, \tilde{y}_t)}.$$

Finally, the agent updates the library based on the current library and this attempt:

$$\mathcal{K}_t = \mathrm{Update\_Library}[\mathcal{K}_{t-1}, (x_t, \tilde{y}_t, \{z_{t-1}\}, \{z_t\})].$$

3.2 Library Representation

The library $\mathcal{K}$ is represented as a weighted collection of knowledge abstractions. It includes two types of knowledge: 1) *modular skills* that can be adapted to solve new tasks. For coding tasks, these are functions; for reasoning tasks, they are sub-problems with corresponding solutions extracted from complete solution trajectories; for agentic tasks, they are sub-tasks with corresponding workflows extracted from complete action trajectories. And 2) *reflective insights* in natural language capturing lessons learned from past trajectories, including common mistakes and corrective strategies (e.g. "If the task involves logistic regression, then do not forget to scale the features").

Sampling. When sampling from the library to solve a new task, we first filter the library entries based on their embedding-based similarity to the task description and then use weighted sampling among the filtered entries based on their weights $w(z \mid \mathcal{K})$. These weights are updated dynamically after generating new solutions for a problem based on the Information Gain and Future Information Gain described in Section 3.2.2.

3.2.1 Extracting Abstractions

We extract *modular skills* $\{z_t\}$ directly from model outputs $\tilde{y}_t$, as these skills are typically *inherent* in the model's reasoning steps either explicitly or implicitly. For coding tasks, we extract functions as skills directly from the synthesized programs. For reasoning and agentic tasks, we extract skills by breaking down the reasoning steps or an action-observation sequence into several sub-modules and summarizing each sub-module into a new, self-contained skill through an LLM call.

To extract *reflective insights* $\{z_t\}$, we first use the LLM itself to estimate the score $S_\Phi(\tilde{y}_t \mid x_t) \in [0, 1]$ for the model solution $\tilde{y}_t$ (with optional textual feedback) [39, 2]. For coding tasks, $S_\Phi(\tilde{y}_t \mid x_t)$ is obtained by instructing the LLM to generate synthetic test cases for the problem x_t and measuring the pass rate of the solution program $\tilde{y}_t$ against the synthetic test. For reasoning tasks, $S_\Phi(\tilde{y}_t \mid x_t)$ is obtained by majority voting [1] and LLM-as-a-Judge [39] to break tie. For multi-turn agentic tasks, the score is obtained by passing the action-observation sequence $\tilde{y}_t$ to the LLM and asking it to judge how many sub-goals in the task x_t have been accomplished. Next, we extract the insights by instructing the LLM to reflect on the solution $\tilde{y}_t$ based on x_t and $S_\Phi(\tilde{y}_t \mid x_t)$ and summarize it into several self-contained insights.

3.2.2 Weighting Mechanism

The core mechanism that enables evolution is credit propagation along the evolution chains of abstractions: useful abstractions not only receive direct reward (through *Information Gain*), but also

Algorithm 1 EVOLIB

Input: Task pool $\mathcal{T}$ of size N, initial library $\mathcal{K}_0 = \emptyset$, model Φ, number of iterations T
Initialize best solutions $\{y_j^*\}_{j=1}^N$ for each task $x_j \in \mathcal{T}$
for t from 1 to T **do**
  Draw a task $x_t \sim \mathcal{T}$ # Solution Generation
  for k from 1 to K **do**
    Sample M abstractions $\{z_{t-1}^{(k)}\} \sim \mathrm{Sample}(\mathcal{K}_{t-1}, x_t)$
    Sample solution trajectory $\tilde{y}_t^{(k)} \sim P_\Phi(\cdot \mid x_t, \{z_{t-1}^{(k)}\})$
    Estimate the accuracy score $S_\Phi(\tilde{y}_t^{(k)} \mid x_t)$
    if $S_\Phi(\tilde{y}_t^{(k)} \mid x_t) > S_\Phi(y_t^* \mid x_t)$ **then**
      $y_t^* \leftarrow \tilde{y}_t^{(k)}$
    end if
  end for
  $k^* \leftarrow \arg\max_k S_\Phi(\tilde{y}_t^{(k)} \mid x_t)$
  $\tilde{y}_t \leftarrow \tilde{y}_t^{(k^*)}$

  $\mathcal{K}_{\mathrm{new}} \leftarrow \mathcal{K}_{t-1}$ # Library Update
  Extract new abstractions $\{z_t\} \leftarrow \mathrm{Extract}(x_t, \tilde{y}_t)$
  for z_t in $\{z_t\}$ **do**
    Compute $\mathrm{IG}(z_t \mid x_t, \mathcal{K}_{t-1})$ based on Eq. (3) if z_t is a skill else 0
    $\mathcal{K}_{\mathrm{new}} \leftarrow \mathrm{Consolidate}[(z_t, \mathrm{IG}(z_t \mid x_t, \mathcal{K}_{t-1})), \mathcal{K}_{\mathrm{new}}]$
  end for
  for z_{t-1} in $\{z_{t-1}^{(k)}\}$ **do**
    Compute $\mathrm{FutureIG}(z_{t-1} \mid x_t, \mathcal{K}_{t-1})$ based on Eq. (6)
    $\mathcal{K}_{\mathrm{new}} \leftarrow \mathrm{Update\_FutureIG}[(z_{t-1}, \mathrm{FutureIG}(z_{t-1} \mid x_t, \mathcal{K}_{t-1})), \mathcal{K}_{\mathrm{new}}]$
  end for
  $\mathcal{K}_t \leftarrow \mathcal{K}_{\mathrm{new}}$
end for
Output: Final library $\mathcal{K}_T$, best solutions $\{y_j^*\}_{j=1}^N$

propagate credit backward to the abstractions that enabled their creation (through *Future Information Gain*). Specifically, we focus on the evolution chains:

$$\{z_1\} \xrightarrow{x_2, \tilde{y}_2} \{z_2\} \xrightarrow{x_3, \tilde{y}_3} \ldots \xrightarrow{x_{t-1}, \tilde{y}_{t-1}} \{z_{t-1}\} \xrightarrow{x_t, \tilde{y}_t} \{z_t\} \xrightarrow{x_{t+1}, \tilde{y}_{t+1}} \ldots,$$

where each step of the evolution $\{z_{t-1}\} \xrightarrow{x_t, \tilde{y}_t} \{z_t\}$ is realized by:

$$\tilde{y}_t \sim P_\Phi(\cdot \mid x_t, \{z_{t-1}\}),\ \{z_t\} = \mathrm{Extract}(x_t, \tilde{y}_t).$$

If $\{z_t\}$ is proven to be useful for producing a high-quality solution for the task x_t, the credit should be propagated not only to the new abstractions $\{z_t\}$, but also to the preceding abstractions $\{z_{t-1}\}, \{z_{t-2}\}, \ldots, \{z_1\}$ along the evolution chain. In practice, to balance between efficacy and computational cost, we propagate the credit by two steps, i.e. to $\{z_t\}$ and $\{z_{t-1}\}$.

More formally, to propagate the credit to $\{z_t\}$, we first define the baseline score for x_t given $\mathcal{K}_{t-1}$:

$$\mu_{\mathrm{base}}(Y \mid x_t, \mathcal{K}_{t-1}) = \mathbb{E}_{\tilde{y}_t, Z_{t-1}}\left[S_\Phi(\tilde{y}_t \mid x_t)\right], \tag{1}$$

where $\tilde{y}_t$ and Z_{t-1} follow $\tilde{y}_t \sim P_\Phi(\cdot \mid x_t, Z_{t-1})$ and $Z_{t-1} \sim \mathrm{Sample}(\mathcal{K}_{t-1}, x_t)$ in the expectation.

We then define the conditional score given that z_t is present in the extracted abstractions:

$$\mu_{\mathrm{cond}}(Y \mid x_t, \mathcal{K}_{t-1}, z_t) = \mathbb{E}_{\tilde{y}_t, Z_{t-1}}\left[S_\Phi(\tilde{y}_t \mid x_t) \mid z_t \in \mathrm{Extract}(x_t, \tilde{y}_t)\right]. \tag{2}$$

Finally, we define **Information Gain (IG)**, which measures how much better the model Φ can solve x_t when z_t is present in the extracted abstractions compared to the average baseline:

$$\mathrm{IG}(z_t \mid x_t, \mathcal{K}_{t-1}) = \log\big(\mu_{\mathrm{cond}}(Y \mid x_t, \mathcal{K}_{t-1}, z_t)\big) - \log\big(\mu_{\mathrm{base}}(Y \mid x_t, \mathcal{K}_{t-1})\big). \tag{3}$$

Furthermore, to propagate the credit back to $\{z_{t-1}\}$, we first define the baseline score where z_{t-1} is not present in the previously sampled abstractions:[2]

$$\mu_{\text{base}}(Y \mid x_t, \mathcal{K}_{t-1}, \overline{z_{t-1}}) = \mathbb{E}_{\tilde{y}_t, Z_{t-1}} \left[S_\Phi(\tilde{y}_t \mid x_t) \mid z_{t-1} \notin Z_{t-1} \right], \tag{4}$$

and the conditional score where z_{t-1} is present:

$$\mu_{\text{cond}}(Y \mid x_t, \mathcal{K}_{t-1}, z_{t-1}) = \mathbb{E}_{\tilde{y}_t, Z_{t-1}} \left[S_\Phi(\tilde{y}_t \mid x_t) \mid z_{t-1} \in Z_{t-1} \right]. \tag{5}$$

And finally, we define **Future IG**, which quantifies how much better the model can solve x_t given z_{t-1} as one of the preceding abstractions, compared to the baseline score:

$$\text{FutureIG}(z_{t-1} \mid x_t, \mathcal{K}_{t-1}) = \log\big(\mu_{\text{cond}}(Y \mid x_t, \mathcal{K}_{t-1}, z_{t-1})\big) - \log\big(\mu_{\text{base}}(Y \mid x_t, \mathcal{K}_{t-1}, \overline{z_{t-1}})\big). \tag{6}$$

Future IG can be interpreted as estimating the contribution of an abstraction to the generation of useful future abstractions.

Overall, we compute the weight of each abstraction z in the library based on its IG and Future IG scores:

$$w(z \mid \mathcal{K}) = \tau \max_{x \in \mathcal{T}} \text{IG}(z \mid x, \mathcal{K}) + \mathbb{E}_{x \sim \mathcal{T}} \text{FutureIG}(z \mid x, \mathcal{K}), \tag{7}$$

where τ is a hyperparameter controlling the relative importance of immediate versus future gain. In practice, we use $\tau = 1$ for all skills and $\tau = 0$ for all insights, as skills can directly contribute to solution construction, whereas insights may not. Future IG is computed for all abstractions (including skills and insights), as both can influence future solution and abstraction generation.

We use the maximum IG over tasks to capture the peak utility of an abstraction, encouraging any abstraction with immediate utility to be sampled and evolve in the future. For Future IG, we take the expectation of Future IG over tasks randomly sampled from the task pool by maintaining a list of Future IG scores for each z, initialized by an empty list. At each iteration, when z_{t-1} is sampled from the library and integrated in the context to solve a task x_t, we compute z_{t-1}'s Future IG given x_t based on Eq. (6) and add it to its Future IG list. When computing $w(z \mid \mathcal{K})$, we estimate the expected Future IG by averaging over the Future IG scores in the list.

Updating Future IG dynamically in this manner makes the agent less prone to the noise in self-evaluated scores, as we take the average over Future IG scores across iterations. It also enables continual evolution of the library – when a more advanced abstraction covering a broader range of use cases emerges, it typically receives high Future IG, while older, less general abstractions exceeded by the new abstraction will receive decreasing Future IG. As a result, more advanced abstractions gradually become more prevalent with higher sampling probability, while older ones are progressively de-emphasized without explicit removal.

3.3 Library Update

Building on the abstraction extraction (Section 3.2.1) and weighting mechanism (Section 3.2.2), we now describe how the library is updated. For each abstraction in the library, we maintain its IG score and a list of Future IG scores obtained on previous tasks. The library is updated in two ways: 1) **abstraction consolidation** where new abstractions are consolidated with similar entries and added to the library, and 2) **updating Future IG** where for each abstraction integrated in the context for solving the current task, we update its Future IG list with the new Future IG score.

Abstraction consolidation. When a new abstraction is extracted from a trajectory, we first retrieve the most similar abstraction of the same type from the library using embedding-based similarity. We then prompt the LLM to consolidate the new abstraction into the most similar one from the library when the abstractions are semantically and functionally similar. If the two abstractions can be merged, the IG and Future IG scores of the old item are also merged into the new consolidated entry. Otherwise, the new abstraction is added as a separate entry (with the current IG score and an empty Future IG list) into the library. This consolidation step is critical for promoting the emergence of abstractions that generalize beyond specific problems.

[2] Note that IG uses the unconditional baseline, while Future IG uses an exclusion baseline to avoid bias introduced by repeated sampling of the same abstraction.

Algorithm 1 summarizes the full procedure, alternating between solution generation and library update (as illustrated in Fig. 1). In the solution generation step, the agent samples a set of abstractions from the current library to construct a contextual prompt, generates and estimates the scores of candidate solutions. In the library update step, newly extracted abstractions are consolidated into the library, and the Future IG scores of the sampled abstractions are updated. The agent iterates through the two steps across successive tasks, enabling the library to continuously grow and evolve.

4 Experiments

4.1 Experimental Setup

Evaluation datasets. We evaluate EvoLib on a diverse set of benchmarks, including mathematical reasoning, code generation, and multi-turn agentic tasks, in two different settings: 1) static benchmarks, where the agent learns through multiple iterations over the whole dataset, and 2) continual learning, where tasks are presented in a stream and each task is attempted only once. In both settings, the agent learns in a self-supervised manner without access to the ground-truth answers or tests.

For the test-time learning setting, we evaluate it on challenging math and coding benchmarks including a) exam questions from Harvard–MIT Mathematics Tournament (**HMMT**) 2025–2026, which is an elite high-school competition featuring complex mathematical reasoning, b) **BigCodeBench Hard** [40], which contains 148 challenging programming tasks designed to evaluate compositional reasoning and the use of existing function calls for real-world programming, and c) **LiveCodeBench v6 Hard** [41], which contains 80 highly challenging competitive coding problems.

For the continual learning setting, we evaluate it on multi-turn agentic tasks, including the **ScienceWorld** [42] and **PDDL** [43] tasks from the AgentBoard benchmark suite [44]. These tasks require multi-round interaction with a partially observable environment. We adopt the task order in the original dataset in our evaluation. See more dataset details in Section A.1.

LLMs. We evaluate the efficacy of EvoLib using both general-purpose LLMs, such as GPT-4o (on BigCodeBench), and LLMs featuring effective reasoning and coding, such as o4-mini (on HMMT, LiveCodeBench, ScienceWorld, and PDDL). On tasks that require intensive reasoning, such as HMMT and LiveCodeBench, we use o4-mini with high reasoning effort, while on multi-turn agentic tasks, we use o4-mini with low reasoning effort.

Baselines. We compare EvoLib against both test-time scaling (TTS) and test-time learning (TTL) approaches. For TTS, we adopt a) **Best-of-N**, which generates N independent solutions and selects the one with the highest estimated accuracy, and b) **Recursive Self-Aggregation (RSA)** [6], which iteratively refines and improves a population of candidate solutions through aggregation of subsets.[3] For TTL, we include **ExpRAG** [9], an agent augmented with a memory of past trajectories and **Dynamic Cheatsheet (DC)** [36], a strong TTL framework that augments an LLM with an evolving textual memory of procedural knowledge.

Evaluation metrics. On HMMT, we evaluate the accuracy of the LLM's solutions against the ground-truth answers using the grading script in [45]. On BigCodeBench and LiveCodeBench, we measure task performance by the pass rate on the true test cases for each problem. On ScienceWorld and PDDL, we adopt the success rate and progress rate from the AgentBoard [44]. On each benchmark, we compare the performance of various methods under the same cost budget measured by weighted token count, where the input token count is weighted by $\lambda = 1$ while the output token count is weighted by $\lambda = 4$.[4]

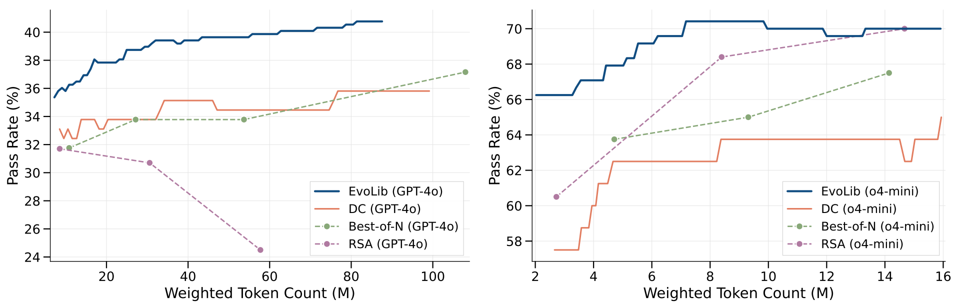
4.2 Main Result: EvoLib Consistently Outperforms Baselines

Comparison on static benchmarks. Table 1 shows that EvoLib achieves the strongest average performance across all evaluated settings, including math, code generation, and multi-turn agentic tasks. In the static setting, EvoLib improves over base sampling by 11-20%, while achieving better or competitive performance compared with the best TTS baseline. On BigCodeBench, GPT-4o

[3] We exclude the TTS baselines on the agentic tasks, as each task is attempted only once through multiple rounds.
[4] The weights are based on the typical per-token rates of input and output tokens for proprietary LLMs.

Table 1: Performance comparing EvoLib against base sampling, test-time scaling (TTS) methods, including Best-of-N and Recursive Self-Aggregation (*RSA*), along with test-time learning (TTL) baselines, including ExpRAG and Dynamic Cheatsheet (*DC*), across math (*HMMT*), coding (*BigCodeBench* and *LiveCodeBench*), and multi-turn agentic tasks (*ScienceWorld* and *PDDL*). For each task, we report the average score over three runs for each method. A dash (–) indicates the method is not applicable to that evaluation setting. An asterisk (*) denotes that the best score(s) is significantly higher than the second-best on each benchmark based on paired student's t-test with $p < 0.05$.

Method	HMMT	BigCodeBench	LiveCodeBench	ScienceWorld		PDDL	
	Accuracy	Pass Rate	Pass Rate	Success	Progress	Success	Progress
Base	57.0	29.7	58.8	53.3	82.9	62.8	79.1
Best-of-N	74.2	37.2	67.5	–	–	–	–
RSA [6]	67.2	31.7	**70.0***	–	–	–	–
ExpRAG [9]	60.2	25.0	51.3	51.1	80.4	39.4	56.7
DC [36]	66.7	35.8	65.0	55.9	83.6	65.0	83.6
EvoLib	**77.4***	**40.8***	**70.0***	**57.4**	**84.3**	**72.8***	**86.2**



(a) BigCodeBench

(b) LiveCodeBench

Figure 2: Cost–performance curves comparing EvoLib with competitive baselines on (a) BigCodeBench and (b) LiveCodeBench. Each curve plots performance (y-axis) as the test-time compute cost (x-axis) increases for each method.

augmented with EvoLib even surpasses the strongest reported LLMs (e.g., *Gemini-Exp-1206* at 40.5%) on the leaderboard. This suggests that test-time learning can substantially close, and in some cases overcome, the gap between less and more powerful base models.

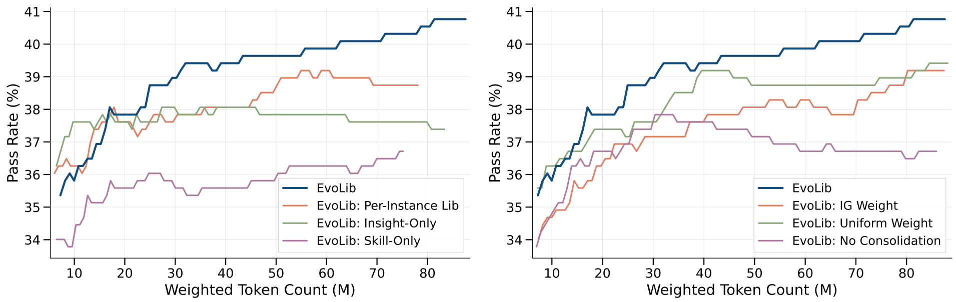
Furthermore, as shown in the cost-performance curves in Figs. 2 and B.1, EvoLib is more token-efficient than both TTS baselines – it yields larger performance gains under tighter cost budgets (+6-16% on BigCodeBench and +3-6% on LiveCodeBench when the budget is reduced by half). These gains indicate that learning and sharing knowledge across problem instances yields consistent improvements over TTS.

Compared to TTL baselines, EvoLib consistently outperforms DC, the best TTL baseline, by 5-10% across three benchmarks. As shown in Fig. 2, it is also more token-efficient than DC.

Comparison in continual learning setting. Table 1 also highlights that EvoLib outperforms all existing TTL methods in the continual learning setting, improving over both ExpRAG and DC baselines. These results demonstrate that EvoLib transfers what it has learned on past tasks to future tasks more effectively than the existing TTL methods.

4.3 Ablation Study

Both abstraction types and cross-instance sharing matter. Fig. 3(a) ablates the types of abstractions stored in the library and how the library is shared. Using only modular skills or only reflective insights underperforms the full variant, which suggests that the two abstraction types contribute complementary value: insights capture higher-level corrective signals that guide future



(a) Ablating Abstraction Types (b) Ablating Weighting and Consolidation

Figure 3: Ablation study on BigCodeBench. (a) Comparison of variants using different abstraction types or per-instance libraries. (b) Comparison of variants with different weighting strategies and without consolidation. Each plot shows the performance in pass rate (y-axis) as a function of test-time compute cost (x-axis).

attempts (especially useful at the early stage), while skills provide solution components that can be reused and recombined to solve more complex tasks. In addition, the per-instance variant lags behind the shared library, especially at larger budgets, which provides strong evidence that the library generalizes beyond problem-specific details. It also supports the claim that cross-problem knowledge reuse and evolution, rather than iterative knowledge refinement within each problem, drives further performance gain.

Abstraction consolidation leads to substantial gain Fig. 3(b) shows the impact of abstraction consolidation. Disabling consolidation hurts performance, particularly as compute increases. We further analyze the role of abstraction consolidation in Section B. Fig. B.2 and Table B.1 indicate that the consolidation step helps control memory growth and turns task-specific abstractions into more generic ones that apply across multiple problems.

Weighting and consolidation are both needed for sustained improvement. Fig. 3(b) also shows the impact of IG and Future IG scores in the weighting mechanism. Uniform weighting leads to weaker scaling at higher compute budgets, where the library grows larger and effective sampling becomes increasingly important. Removing the Future IG score also degrades performance substantially, as it is crucial for selecting abstractions that can evolve into more advanced ones.

4.4 Robustness To Task Ordering

We further study robustness to task ordering in the continual learning settings on PDDL, which contains multiple distinct task types (see Table B.2 and discussion in Section B for details). We find that EvoLib consistently outperforms DC across easy-to-hard, hard-to-easy, and random task streams, with the largest gain (+9%) under random ordering. The result indicates that EvoLib can continually learn from diverse tasks even when they are interleaved, suggesting its practical advantage in real-world scenarios where an agent must handle and learn from a mixed stream of heterogeneous user requests without relying on a structured curriculum.

5 Discussion

This paper introduces EvoLib, a framework that enables black-box LLMs to self-improve at test time through abstraction induction, reuse, and evolution. A key property of EvoLib is its favorable scaling behavior: performance improves consistently as more problems are solved and more compute is invested, without external supervision. This draws a direct analogy to human cognitive development. Just as humans build progressively more abstract mental models through experience, the library evolves from concrete, task-specific functions toward more general, reusable abstractions. Experiments on mathematical reasoning, code generation, and interactive agentic tasks show that EvoLib consistently outperforms existing test-time scaling and test-time learning methods with lower token cost. The framework offers a promising direction for LLMs to learn and self-improve during deployment without requiring gradient-based fine-tuning or supervision signals.

Limitations. The current EvoLib framework assumes that the model's own judgment of a solution provides more useful signals than noise for self-evaluation. Thus, the method works best for tasks in which verifying a solution is easier than generating one (e.g., coding tasks with executable test cases). For tasks where verification requires comparable or even greater effort than solution generation, a powerful external verifier model may be necessary to reliably assess each candidate solution. Additionally, the current evaluation focuses on math, coding, and agentic tasks. It is unclear how well the approach generalizes to other domains, such as open-ended question-answering or scientific tasks, with different knowledge types and feedback characteristics.

Future work. One promising direction is to enable LLMs to meta-learn the design of the library itself, including the choice of abstraction forms, the weighting mechanism, and the library update algorithm. Rather than fixing these components, the system could optimize them over time based on previous tasks and sampled trajectories, the structure of the task stream, potentially leading to more efficient test-time learning schemes. Another direction is to deploy the framework in long-horizon settings with a mixed stream of diverse tasks. Such settings would better reflect real-world usage and help identify challenges related to scalability, distribution shift, and knowledge retention.

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Table A.2: Summary of datasets used in evaluation.

Domain	Dataset	# Instances	Notes
Math Reasoning	HMMT Feb 2025	30	Competitive math problems
	HMMT Nov 2025	30	Competitive math problems
	HMMT Feb 2026	33	Competitive math problems
	HMMT (Total)	93	Competitive math problems
Code Generation	BigCodeBench Hard	148	Real-world programming problems
	LiveCodeBench v6 (Hard)	80	Competitive programming problems
Agentic Tasks	ScienceWorld	90	Scientific experiment tasks
	PDDL	60	Symbolic planning tasks

A Experimental Setup Details

A.1 Dataset Details

We evaluate our method on a diverse set of benchmarks spanning mathematical reasoning, code generation, and multi-turn agentic tasks. All datasets used in this work are publicly available.

For mathematical reasoning, we use exam problems from the `Harvard-MIT Mathematics Tournament (HMMT)`, an elite high-school competition featuring challenging mathematical reasoning questions spanning algebra, combinatorics, geometry, and number theory. Specifically, we combine problem sets from three recent competitions: February 2025, November 2025 and February 2026, all obtained from the `MathArena` collection on HuggingFace.[5] We evaluate performance using accuracy against ground-truth answers, following the official grading scripts provided by `MathArena`.

For code generation, we evaluate on the `BigCodeBench Hard` benchmark, a subset of BigCodeBench designed to assess real-world programming and compositional reasoning abilities,[6] and `LiveCodeBench`, a benchmark of competitive programming problems.[7] Performance is measured using pass@1-style accuracy (pass rate), i.e., whether the generated program passes all ground-truth (including hidden) test cases.

For evaluating multi-turn agentic behavior, we use tasks from the AgentBoard benchmark suite.[8] Specifically, we evaluate on `ScienceWorld`, a simulated environment requiring sequential decision-making and scientific reasoning, and `PDDL`, symbolic planning tasks defined in the Planning Domain Definition Language. Each task involves multi-step interaction with an environment, where the model generates actions conditioned on observations. Tasks are partially observable and require planning over multiple turns. We evaluate performance using the success rate (whether the task is completed) and progress rate (fraction of sub-goals achieved) provided by AgentBoard.

Table A.2 summarizes the information of each dataset.

A.2 Model Details

We use GPT-4o (version `2024-11-20`) [46] with a temperature of 0 and $top\_p = 0.5$ on BigCodeBench. On ScienceWorld and PDDL, we use o4-mini (version `2025-04-16`) with low reasoning effort.[9] On LiveCodeBench and HMMT, we use o4-mini (version `2025-04-16`) with high reasoning effort.

A.3 Baseline Details

We compare our method against representative test-time scaling (TTS) and test-time learning (TTL) methods. For TTS, we include Best-of-N sampling, which generates N independent candidate solutions per task and selects the one with the highest self-estimated score. We also evaluate Recursive Self-Aggregation (RSA) [6], a stronger TTS method that iteratively refines a population of reasoning trajectories by aggregating subsets of candidates, enabling progressive improvement across iterations. We run it with the population size $N = 16$ and aggregation subset size $K = 4$ with GPT-4o and o4-mini to balance between inference cost and performance. For TTL

[5] `https://huggingface.co/datasets/MathArena/hmmt_feb_2025`, `https://huggingface.co/datasets/MathArena/hmmt_nov_2025`, `https://huggingface.co/datasets/MathArena/hmmt_feb_2026`

[6] `https://huggingface.co/datasets/bigcode/bigcodebench-hard`

[7] `https://github.com/LiveCodeBench/LiveCodeBench` (we use the hard subset of v6).

[8] `https://hkust-nlp.github.io/agentboard/`

[9] `https://openai.com/index/o3-o4-mini-system-card/`

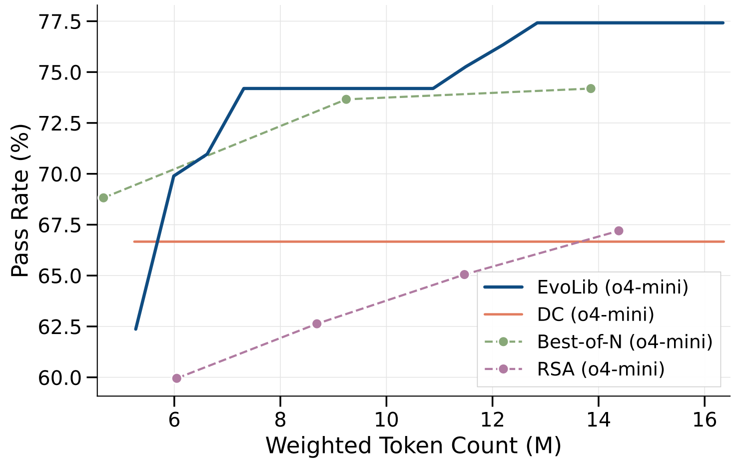


Figure B.1: Cost–performance curve comparing EvoLib with competitive baselines on HMMT. Each curve plots performance (y-axis) as the test-time compute cost (x-axis) increases for each method.

baselines, we include ExpRAG [9],[10] which augments the base model with a global memory of raw trajectories, and Dynamic Cheatsheet [36],[11] which maintains an adaptive memory (i.e. a cheatsheet) of high-level principles and procedural knowledge extracted through self-reflection. For all baselines, we run them with varying token cost budget (i.e. varying N for Best-of-N and varying number of iterations for the other methods) and compare performance under the same cost budget.

A.4 EvoLib Details

To estimate the baseline and conditional scores, the agent typically samples multiple times for each problem x_t, except for the continual learning experiments where the agent attempts each task only once. In this case, the agent uses samples at previous turns for the same task to estimate the scores. We set the number of trials $K = 3$ on code generation tasks, and $K = 10$ for mathematical reasoning, while on multi-turn agentic tasks, each task is attempted only once (following the continual learning setting). To retrieve similar functions for abstraction consolidation, we set the embedding-based similarity threshold to 0.8. For weighted sampling, we sample at most 10 insights and 10 skills into the LLM prompt, and set the task-abstraction similarity threshold to 0.2 on agentic tasks and to 0 on the other benchmarks (since the problems within each benchmark are highly related on these benchmarks). We use *text-embedding-3-small* as the embedding model.

B Extended Results

Cost-Performance Curve on HMMT. Fig. B.1 shows the cost–performance curve on HMMT. EvoLib maintains a consistent advantage across the compute range, similar to the trends observed on coding benchmarks in the main paper. Although EvoLib adds an average of 1-2 LLM calls per iteration for scoring, maintaining and updating the library, it improves performance more rapidly with fewer attempts than the TTS approaches.

Library growth and the role of consolidation. Fig. B.2 compares the growth of the library with and without consolidation. Without consolidation, the number of entries increases nearly linearly with the number of iterations, reflecting the accumulation of task-specific abstractions. In contrast, with consolidation, the growth is substantially slower at later stage. Case 3 in Table B.1 provides a concrete example of the consolidation process. A newly extracted function and an existing function are merged into a more general abstraction that subsumes both behaviors. This illustrates how the library evolves from specific, task-level functions into abstractions that apply across multiple problems. Such generalization is central to enabling transfer across tasks without explicit supervision. These results support the role of consolidation in controlling memory growth while encouraging the emergence of generic abstractions.

Evolution of abstraction quality. Fig. B.3 examines how the quality of the most useful abstractions evolves over time. Both the average IG and average Future IG among the top entries increase as the number of iterations grows. The increase in IG indicates that the library progressively contains abstractions that directly

[10] We set the number of retrieved entries to 4 as recommended and use *text-embedding-3-small* as the embedding model.

[11] We use the *DC-Cumulative* variant in all our experiments as it outperforms the other variant in the preliminary experiment.

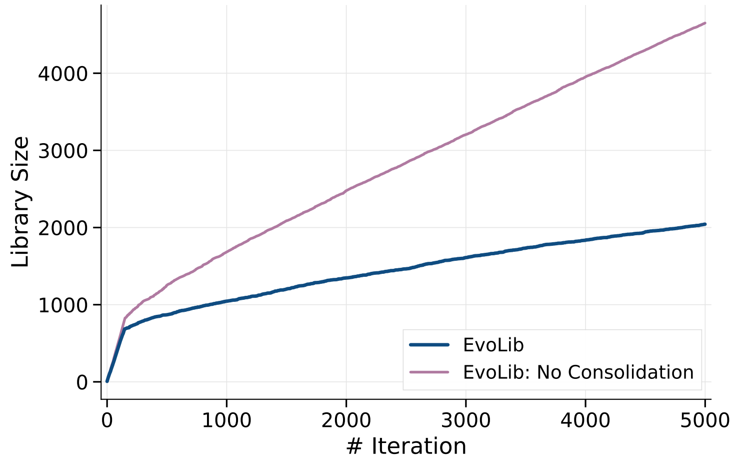
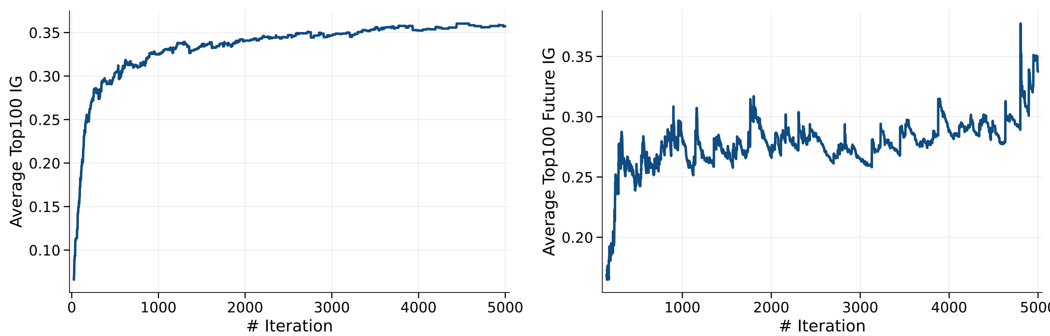


Figure B.2: Growth of the library size over iterations with and without consolidation on BigCodeBench. The x-axis shows the number of iterations and the y-axis shows the number of abstractions stored in the library.



(a) Average IG Among Top 100 Entries

(b) Average Future IG Among Top 100 Entries

Figure B.3: Average Information Gain (IG) and Future Information Gain (Future IG) among the top 100 abstractions in the library over iterations on BigCodeBench. The x-axis shows the number of iterations and the y-axis shows the average score for the top-ranked abstractions.

improve solution quality. The increase in Future IG suggests that the library also becomes better at generating abstractions that enable further learning. Together, these trends provide evidence that the weighting mechanism prioritizes abstractions that contribute both immediate and future utility.

Effect of task order in continual learning. Table B.2 compares EvoLib with Dynamic Cheatsheet (DC) under different task orders, including easy-to-hard, hard-to-easy, and random permutations. EvoLib consistently outperforms DC across all settings, achieving higher success rates and progress rates. Notably, the advantage is largest under random ordering, where no curriculum structure is present, suggesting that EvoLib is more robust to variations in the task stream.

Importantly, since PDDL comprises four different types of tasks that require different types of actions and planning strategies, strong performance under random ordering indicates that EvoLib can effectively handle and continually learn from a heterogeneous mixture of task types without relying on a structured curriculum. This property is desirable in real-world scenarios, where an agent must respond to diverse user requests in arbitrary order and still accumulate useful abstractions over time.

Overall, these results support the hypothesis that EvoLib enables continual learning that is less dependent on task ordering, whereas methods based on linear knowledge updates are more sensitive to the ordering.

EvoLib addresses the failure modes in continuously updated abstract memory. Recent work shows that continuously updated abstract memory in existing approaches can degrade performance through three major failure modes: *misgrouping*, where experiences from different types of tasks are consolidated into the

	Consolidation Case Study
1	**(Over-generalized → Grounded)** **Old Insight:** If you need to move multiple objects between two rooms and have two free grippers, then pick up two different objects in the source room before moving, so you can carry both in one trip. **New Insight:** If both grippers are free and there are objects in the same room that need relocation, then use both grippers simultaneously to pick objects, reducing the number of move–drop cycles. **Consolidated Insight:** If both grippers are free and there are multiple objects in the same room that need relocation, then pick up two different objects simultaneously before moving, so you can carry both in one trip and reduce the number of move–drop cycles.
2	**(Over-generalized → Grounded)** **Old Insight:** If a calculated metric such as AUC or any other value can result in NaN due to invalid inputs or edge cases, then handle such cases explicitly (e.g., skipping computation, default values, or raising errors). **New Insight:** If a metric (e.g., AUC) can result in NaN due to edge cases (e.g., all true labels are the same → undefined ROC), then explicitly detect and handle this condition. **Consolidated Insight:** If a calculated metric such as AUC or any other value can result in NaN due to invalid inputs or edge cases, such as all true labels being the same leading to an undefined ROC curve, then handle such cases explicitly (e.g., skipping computation, default values, or raising meaningful errors).

3	**(Overfitting → General)**
	Old Skill:
	`def validate_dataframe_columns(data, min_columns):`
	`  if not isinstance(data, pd.DataFrame):`
	`    raise ValueError(...)`
	`  if data.shape[1] < min_columns:`
	`    raise ValueError(...)`
	New Skill:
	`def validate_minimum_categories(data, columns, min_categories=2):`
	`  for col in columns:`
	`    if data[col].nunique() < min_categories:`
	`      raise ValueError(...)`
	Consolidated Skill:
	`def validate_dataframe(data, min_columns=None, column_category_constraints=None):`
	`  if not isinstance(data, pd.DataFrame):`
	`    raise ValueError(...)`
	`  if min_columns is not None:`
	`    if data.shape[1] < min_columns:`
	`      raise ValueError(...)`
	`  if column_category_constraints is not None:`
	`    for col, k in column_category_constraints.items():`
	`      if col not in data.columns:`
	`        raise ValueError(...)`
	`      if data[col].nunique() < k:`
	`        raise ValueError(...)`

Table B.1: Consolidation cases illustrating generalization and grounding effects in EvoLib.

same abstraction; *interference*, where repeated rewriting strips away applicability conditions and turns useful lessons into overly broad guidance; and *overfit*, where memory becomes tied to narrow surface patterns rather than reusable strategies [38]. By contrast, our experiments show that EVOLIB avoids or substantially alleviates these issues:

Misgrouping. EVOLIB is less susceptible to misgrouping because its consolidation is localized rather than global: two abstractions are merged only when they are close in the embedding space and are judged semantically and functionally similar. Table B.2 provides further evidence: EVOLIB remains strong even under random task ordering in PDDL, where four task types are interleaved, suggesting that the library can accumulate useful abstractions from a heterogeneous stream without requiring a clean curriculum to keep different task families separated.

Interference. The interference failure mode arises when repeated rewriting and consolidation remove the conditions under which a lesson is valid, causing an abstraction learned from one setting to mislead behavior in another. EVOLIB mitigates this effect as it extracts an abstraction from one trajectory at a time and only

Table B.2: Success and Progress Rate on PDDL under different task orders. We report mean ± standard deviation over three runs for each method.

Method	**Easy → Hard**		**Hard → Easy**		**Random**	
	Success	Progress	Success	Progress	Success	Progress
DC	66.7 ± 2.9	82.2 ± 2.5	65.6 ± 1.9	80.7 ± 0.6	65.6 ± 1.0	81.5 ± 0.8
EvoLib	**71.1 ± 2.5**	**85.5 ± 3.0**	**68.9 ± 4.8**	**86.3 ± 0.7**	**74.4 ± 1.9**	**88.1 ± 1.5**

consolidates it with another abstraction when they are semantically and functionally similar. Case 1 and 2 in Table B.1 show that the consolidation process in EvoLib can move abstractions in the opposite direction: it adds more grounded conditions to the insight statements rather than smoothing them away into generic advice. In addition, an abstraction that interferes with a broad range of tasks will receive low Future IG scores, decreasing its chance to be sampled during inference. As shown in Tables B.3 to B.7, the top high-Future-IG abstractions remain concrete and applicable to only a subset of tasks.

Overfit. The overfit failure mode occurs when memory tracks recurring surface regularities of past instances instead of extracting a strategy that transfers to related tasks. This problem is mitigated in EvoLib by the consolidation and weighting mechanism. An abstraction that is specific to a certain task can be consolidated with a new one (from a related but different task) into a more general abstraction, as shown by Case 3 in Table B.1. Furthermore, abstractions that remain overly specific will then receive low Future IG scores and thus low sampling weights. As shown in Tables B.3 to B.7, the highest-Future-IG entries are typically reusable procedures, checks, or reasoning templates that are applicable to similar tasks.

	Top Insights (BigCodeBench)
1	If (your function or program processes input that requires specific formatting or encoding, such as hexadecimal strings or UTF-8 encoded data), then (handle potential decoding errors gracefully by implementing checks and providing meaningful error messages before proceeding with further processing).
2	If a function depends on external systems (e.g., network, file I/O, or hardware) to produce results, then ensure to mock or simulate these external dependencies during testing to avoid false negatives caused by environmental factors or unhandled edge cases.
3	If (a function interacts with a directory or file system), then consider the case (the directory or file may not exist) and handle it explicitly by checking for existence before performing operations, or by using try-except blocks to catch and handle `FileNotFoundError` or similar exceptions.
4	If (a function processes external files or data inputs), then ensure to validate the existence, format, and content of the files or data before proceeding with further operations. Specifically, check for conditions such as file existence, non-empty content, and adherence to expected structure or format. Handle errors gracefully by providing meaningful error messages, consider edge cases like empty files or missing data to prevent runtime exceptions, raise appropriate exceptions or provide fallback mechanisms for invalid data, and explicitly handle cases where the input might be empty, corrupted, or invalid.
5	If your code involves calculating metrics like AUC or other statistical measures, then ensure that the input data (e.g., true labels and predicted probabilities) is valid and does not contain edge cases such as all true labels being the same class (e.g., all 0s or all 1s) or predicted probabilities being constant, as these can result in undefined or NaN values. Consider adding checks to validate the input data and handle such cases explicitly, such as skipping the calculation, providing a meaningful default value, or raising an informative error.
	Top Skills (BigCodeBench)
1	`def validate_range(range_low, range_high):` `""" Validate that the lower bound is less than the upper bound.  Parameters:  range_low (int):  Lower bound of the range.  range_high (int):  Upper bound of the range.  Raises: ValueError:  If range_low is not less than range_high.  """`
2	`def fetch_and_prepare_boston_data(data_url):` `""" Fetches and prepares the Boston Housing dataset from the given URL. Parameters: data_url (str):  URL to the Boston Housing dataset.  Returns:  pd.DataFrame:  A DataFrame containing the prepared Boston Housing data.  """`
3	`def task_func(kwargs, target_dir="non_none_files"):` `""" Process files from a dictionary by checking if the file exists, and if it has content, then copies it to a target directory.  Parameters:  kwargs (dict):  dictionary of file paths to content.  target_dir (str):  destination directory.  Returns:  list of copied file paths.  """`
4	`def task_func(df, target_column):` `""" Train a random forest classifier to perform classification and plot feature importances.  The plot uses feature importance scores on the x-axis and feature names on the y-axis, sorted in descending order.  Returns the trained model and plot Axes.  """`
5	`def encrypt_aes_key_with_rsa(aes_key, public_key):` `""" Encrypts an AES key using an RSA public key.  Parameters:  aes_key (bytes):  The AES key to encrypt.  public_key (rsa.PublicKey):  The RSA public key.  Returns:  bytes:  The encrypted AES key.  """`

Table B.3: Top insights and skills with high Future IG in EvoLib on BigCodeBench.

	Top Insights (LiveCodeBench)
1	If you're maintaining counts of available items by splitting them into "below" and "above" a moving threshold, then after picking an item you must decrement the count of whichever subgroup it came from (or adjust your pointer), not just the total used count, so your future availability calculations remain correct.
2	If you define a block in Python (such as a function, class, loop, or conditional) ending with a colon, then do include at least one indented statement (even just a `pass`) immediately after, otherwise you'll get an "expected an indented block" syntax error.
3	If you split your digit-DP into two passes (one for numbers that contain a special digit and one for numbers that don't), then do not treat every zero the same—use a "started" flag so that leading zeros aren't counted as actual zeros, only set your "have_zero" flag when you see a zero after you've "started," and in the zero-free pass forbid zeros once "started." This way your two DPs form a disjoint, exhaustive partition and you won't undercount or overcount any numbers.
4	If your problem involves multiple agents that cannot occupy the same vertex at the same time—but may visit the same vertex at different times—then do not model these conflicts as permanent vertex-capacity constraints. Instead, you must encode the temporal dimension (for example by building a time-expanded graph or by BFS on the joint (position,time) state).
5	If you're using binary search to maximize or minimize an integer parameter via a feasibility predicate, then verify that your initial bounds cover the entire range of possible values, ensure the predicate is monotonic, and test edge cases; otherwise you may cut off the real optimum or get the wrong threshold.
	Top Skills (LiveCodeBench)
1	`def greedy_interval_cover(sorted_intervals, cover_L, cover_R):` `""" Greedy interval covering algorithm. Given intervals sorted by left endpoint, selects a minimum-cardinality sub-collection that covers [cover_L, cover_R]. Returns selected indices or empty list if impossible. """`
2	`def divisors_from_prime_counts(prime_counts: dict) -> list:` `""" Generate all divisors of a number from its prime factorization using DFS over prime powers. """`
3	`def kmp_search(text, pattern):` `""" Return True if pattern occurs in text using the KMP algorithm. Time complexity: O(len(text) + len(pattern)). """`
4	`def tarjan_scc(graph):` `""" Compute strongly connected components of a directed graph using Tarjan's algorithm. Returns a list of components. """`
5	`def binary_search_last_true(lo, hi, pred):` `""" Given a monotonic predicate pred(x), find the maximum x in [lo, hi] such that pred(x) is True. """`

Table B.4: Top insights and skills with high Future IG in EvoLib on LiveCodeBench.

	Top Insights (HMMT)
1	If a single oriented half-space on two parallel convex polygons selects "sup–blocks" of vertices, then those blocks on the two polygons must share the same extremal index (they start at the same vertex) unless one of the blocks is empty or the entire polygon.
2	If you use inclusion–exclusion to count "bad" subsets defined by forbidden substructures (cuts, patterns, etc.), you must list and include all minimal forbidden substructures—in particular those of higher cardinality that do not contain smaller ones—to avoid undercounting.
3	If a point induces two triangles with a common "angle-ratio" condition and known side-length ratio, then view the situation as a spiral similarity centered at that point—write its rotation angle and scale factor explicitly, and impose the "sum of the four angles around a point equals 360°" to link the small triangle's base angle to the given interior angle.
4	If you use the Law of Sines in two triangles sharing no common angle, then a ratio of side-lengths such as BP/PC generally equals a product of three sine-ratios, not simply sin x/sin y. Always carry along the extra factors from both sine laws.
5	If you need the sign of sin(x) by comparing x to multiples of π, then use floor(x/π) mod 2: sin(x)$>$0 exactly when floor(x/π) is even. Moreover, parity (floor($2^n \cdot \alpha$)) equals the nth binary digit of α.
	Top Skills (HMMT)
1	**Eliminate variables by combining constraints:** When you have two constraints (e.g., a right-angle/power relation plus a circle/quadratic relation), substitute one into the other to eliminate a squared term and derive a simpler (often linear) relationship among the remaining variables.
2	**Exploit symmetry to reuse a count:** If a configuration has an involutive symmetry (swapping roles, reversing a half-space, etc.), map the "opposite case" to the original one to conclude both cases contribute equally, rather than recounting from scratch.
3	**Re-encode divisibility as a product order:** For sets defined by prime-power structure, represent elements by exponent vectors; then divisibility becomes coordinatewise comparison, turning the problem into reasoning about a product of chains (a grid poset).
4	**Parameterize points on a segment affinely:** To locate points at specified distances along a segment, express each point as an affine combination $P = (1-t)B + tC$ with t equal to the normalized arc-length fraction; then read off coordinates or derived quantities cleanly.
5	**Reduce interacting motion to a standard stochastic process:** When multiple moving objects merge upon contact, reinterpret the dynamics as coalescing random walks (or an equivalent Markov process) on an appropriate state space, enabling use of known results or simpler expectation calculations.

Table B.5: Top insights and skills with high Future IG in EVOLIB on HMMT.

	Top Insights (ScienceWorld)
1	If you are navigating to a known target location, then first confirm the correct connecting doorway by using "look around" in your current room, plan the most direct route, and avoid back-and-forth movements that don't add information.
2	If you need to choose among multiple objects, first list or note all candidates, then compare their key attributes (e.g. life span) before focusing on one.
3	If you intend to select from an ambiguity menu, do not type just the index; you must include the action keyword plus the exact indexed object name.
4	If you have heated an ingredient and see "Progress 0.5/1.0," then check with the appropriate measuring device to complete the task.
5	If a substance must reach a phase change, then ensure the heating source is fully activated and give sufficient waiting time (or confirm rising temperature) before checking for melting.
	Top Skills (ScienceWorld)

1	**Functionality:** Heat a substance in a container using the stove until it reaches or exceeds a target temperature.
	Condition: When you need to raise the temperature of whatever is in the vessel to a desired threshold.
	Input Variables: Stove, Thermometer, Vessel, TargetTemp.
	Steps:
	`move Vessel to Stove`
	`activate Stove`
	`wait1`
	`wait1`
	`wait1`
	`use Thermometer on Vessel`
	`(if temperature < TargetTemp, repeat wait and measure)`
	`deactivate Stove`

2	**Functionality:** Deliver or deposit an object from your inventory into a target container.
	Condition: When you have the object in inventory and need to place it into a named container.
	Input Variables: OBJ, DEST_LOC, CONTAINER.
	Steps:
	`(if not at DEST_LOC) go to DEST_LOC`
	`look around`
	`move OBJ to CONTAINER`

3	**Functionality:** Retrieve an item from a storage container.
	Condition: When an object needed for a task is inside a container.
	Input Variables: OBJ, CONTAINER.
	Steps:
	`open CONTAINER`
	`look in CONTAINER`
	`pick up OBJ`

4	**Functionality:** Verify the physical state of a substance after a process.
	Condition: After performing a process intended to change a substance's state (e.g., heating or freezing).
	Input Variables: STORAGE, CONTAINER, SUBSTANCE.
	Steps:
	`(if STORAGE exists) open STORAGE`
	`open CONTAINER`
	`look in CONTAINER`
	`focus on SUBSTANCE`
	`look at SUBSTANCE`

5	**Functionality:** Wait until an object changes state over time.
	Condition: When an environmental or physical process requires time to complete.
	Input Variables: desired_state.
	Steps:
	`wait`
	`(or) wait1`
	`look around`
	`repeat until state changes`

Table B.6: Top insights and skills with high Future IG in EvoLib on ScienceWorld.

	Top Insights (PDDL)
1	If working with nuts on a hub, then jack up the hub before undoing or removing the wheel; after wheel removal or installation, refasten the nuts and jack down; and ensure the hub is on the ground before tightening any loose nut.
2	If you leave a shot glass on the table after cleaning, then you can pour into it directly from a shaker without grasping it, as long as you satisfy the hand-holding requirements of the pour action.
3	If you finish dropping the last carried object, then check immediately for any remaining objects in the other room to avoid idle moves.
4	If the hub is on the ground, then you must loosen the nuts before jacking up; otherwise removal is impossible.
5	If a block you want is not on the table, then unstack it from whichever block it's on before attempting to pick it up.
	Top Skills (PDDL)

1	**Functionality:** Load two specified ingredients into a clean shaker using two separate shot glasses.
	Condition: The shaker is clean and empty; both shot glasses are clean and empty; both hands are empty; dispensers are available.
	Input Variables: shot1, ingredient1, shot2, ingredient2, hand, other_hand, shaker, dispenser1, dispenser2, l0, l1, l2.
	Steps:
	`hand grasp shot1`
	`fill-shot shot1 ingredient1 hand other_hand dispenser1`
	`pour-shot-to-clean-shaker shot1 ingredient1 shaker hand l0 l1`
	`clean-shot shot1 ingredient1 hand other_hand`
	`fill-shot shot2 ingredient2 hand other_hand dispenser2`
	`pour-shot-to-used-shaker shot2 ingredient2 shaker hand l1 l2`
	`hand leave shot2`

2	**Functionality:** Remove a wheel from a hub and stow it in the boot.
	Condition: The hub is on the ground, the nut is tight, tools are available, and the boot is open.
	Input Variables: hub, wheel, nut, boot.
	Steps:
	`loosen nut hub`
	`jack-up hub`
	`undo nut hub`
	`remove-wheel wheel hub`
	`put-away wheel boot`
	`jack-down hub`

3	**Functionality:** Fetch the basic tools (wrench and jack) from a closed container.
	Condition: The container is closed but unlocked, and tools are inside.
	Input Variables: container, wrench, jack.
	Steps:
	`open container`
	`fetch wrench container`
	`fetch jack container`

4	**Functionality:** Move a block from one block to another.
	Condition: The arm is empty; block X is clear and on block U; block V is clear.
	Input Variables: X, U, V.
	Steps:
	`unstack X U`
	`stack X V`

5	**Functionality:** Shake a two-ingredient mixture in a shaker to form a cocktail.
	Condition: The shaker contains the correct ingredients and is unshaken.
	Input Variables: cocktail, ingredient1, ingredient2, shaker, hand1, hand2.
	Steps:
	`hand1 grasp shaker`
	`shake cocktail ingredient1 ingredient2 shaker hand1 hand2`

Table B.7: Top insights and skills with high Future IG in EvoLib on PDDL.

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