Augmenting Language Agents with Parametric Memory

Tianjun Yao[1] **Yongqiang Chen**[1,2] **Yujia Zheng**[2] **Zhiqiang Shen**[3] **Pan Li**[3] **Kun Zhang**[1,2]

[1]Mohamed bin Zayed University of Artificial Intelligence
[2]Carnegie Mellon University [3]Georgia Institute of Technology

Abstract

Large Language Models (LLMs) have demonstrated strong reasoning abilities, yet existing agent frameworks remain constrained by two limitations. First, they typically operate at the per-instance level, confining signals to individual problems and overlooking transferable patterns across tasks. Second, while some approaches attempt to incorporate global information through external memory, these are non-parametric in nature, and thus capture only shallow interactions across instances, failing to uncover deeper regularities. To overcome these limitations, we propose `ParamAgent`, a language agent framework that leverages a domain-adaptive parametric memory to internalize knowledge across samples into model parameters. In addition to capturing cross-sample regularities, `ParamAgent` provides twofold flexibility: (i) the parametric module can supply different forms of knowledge depending on various domains, and (ii) the same module can be integrated with different base LLMs, making `ParamAgent` broadly applicable. Moreover, `ParamAgent` naturally promotes diversity of outputs by adjusting the sampling temperature of the parametric module. Experiments on programming, math reasoning, and multi-hop question answering benchmarks show that `ParamAgent` consistently outperforms state-of-the-art baselines, surpassing the best baseline by up to 7.90%, 9.41%, and 24.30% respectively.

1 Introduction

Large language models (LLMs) [6, 10, 31] have exhibited striking progress in complex reasoning tasks. Their ability to interleave reasoning with actions has led to the development of autonomous language agents that treat an LLM as the core policy[37, 28, 43, 42, 49, 22, 38, 32, 15, 46]. For example, Chain-of-Thought (CoT) prompting [37] elicits explicit intermediate steps that improve reasoning performance on complex tasks. Self-Refine [22] introduces an iterative self-feedback loop, enabling models to progressively refine their outputs and achieve higher-quality results. Subsequent work expands agents' search and feedback mechanisms: Reflexion [28] stores verbalized feedback in episodic memory (i.e., a long-term memory of the agent's self-reflections accumulated across iterations) and yields noticable gains; Tree-of-Thoughts (ToT) [42] explores multiple reasoning paths via tree search; LATS integrates Monte-Carlo Tree Search for long-horizon planning [49, 7].

Despite the effectiveness of self-reflection, recent work has identified a lack of diversity in the reflective signals as the limitation [19]. To address this, [19] has proposed DoT and DoT-bank, which enhance reflective diversity through prompt-level variation and retrieval-based cross-sample trajectories. Similarly, many previous work propose to use textual log as external memory to enrich the reflective inputs, therefore enhancing the reasoning ability of language agent [5, 27, 34, 27, 48, 36]. These results confirm that introducing diverse reflective information can substantially improve the agent's reasoning process. However, prompt-based approaches cannot

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capture cross-sample regularities, and retrieval-based methods using external memory may be constrained by the limited number and coverage of stored samples. This naturally raises the question:

How can we further expand reflective diversity to achieve stronger reasoning performance?

To overcome these limitations, we propose `ParamAgent`, a language-agent framework that leverages parametric knowledge. `ParamAgent` introduces an external module M_* (where $*$ denotes different knowledge types across domains) to internalize cross-sample information. When solving a new problem, the agent queries M_* to obtain population-level insights rather than purely instance-level feedback. For example, M_r can synthesize common error patterns for programming and math tasks, while M_p generates semantic decomposition units for multi-hop question answering (Sec. 3). As the parametric knowledge is encoded directly into the parameters of M_* through training, the module captures cross-sample regularities and produces reflective signals that differ fundamentally from self-reflection and retrieval-based trajectories. This parametric module introduces an additional layer of diversity into the reflective inputs. As we will show in Sec. 4, this additional form of diversity works jointly with reflection-based frameworks and further enhances the agent's reasoning ability. Beyond diversity, `ParamAgent` offers two forms of flexibility. First, M_* can generate different types of knowledge, from population-level reflective feedback to structured semantic units. Second, the same parametric module can be paired with different base LLMs, making `ParamAgent` broadly applicable across architectures and domains.

We evaluate `ParamAgent` on math reasoning problems, programming, and multi-hop QA. In each domain, `ParamAgent` significantly outperforms state-of-the-art methods. Concretely, our approach surpasses the best baseline by up to 7.90% on programming, 9.41% on math reasoning, and 24.30% on multi-hop QA. Our contributions can be summarized as follows:

- We identify key limitations in existing agent frameworks and propose leveraging parametric knowledge to capture cross-sample interactions, thereby augmenting the reasoning process.
- We propose `ParamAgent`, a language agent that equips a parametric module to capture cross-sample regularities, and further introduce `ParamAgent-plus`, an enhanced variant that integrates multiple forms of memory modules.
- The parametric module M_* is capable of synthesizing multiple forms of knowledge that support adaptation to a wide range of domains, and it can be flexibly integrated with different base LLMs in the agents.
- Through extensive experiments on programming, math reasoning, and multi-hop QA, `ParamAgent` consistently outperforms state-of-the-art baselines, surpassing the second best by up to 7.90%, 9.41%, and 24.30% respectively.

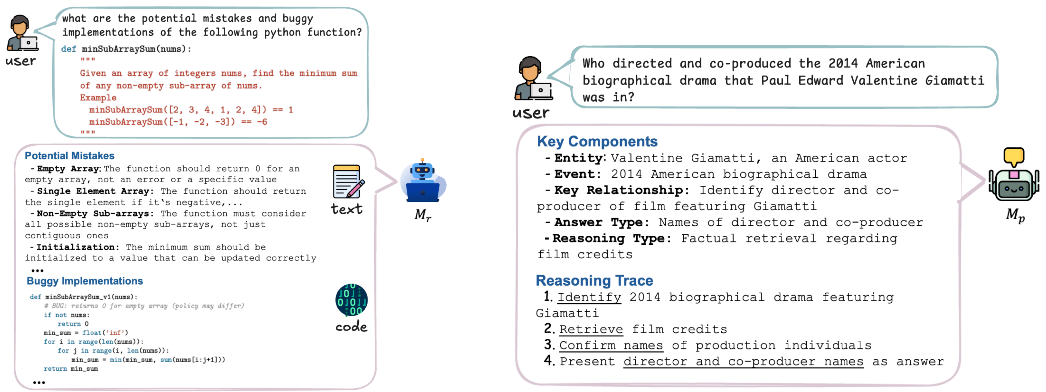
2 Preliminaries

We consider a pretrained Language Model (LM) p_θ with parameters θ that operates on token sequences. Let $x = (x[1], \ldots, x[l_x])$ denote the input sequence and $y = (y[1], \ldots, y[l_y])$ the output sequence. The LM decodes autoregressively, i.e., $p_\theta(y \mid x) = \prod_{i=1}^{l_y} p_\theta\big(y[i] \mid x, y[1{:}i{-}1]\big)$, and, more generally, with an auxiliary prompt π (e.g., instructions, exemplars, tool feedback, etc.), $p_\theta(y \mid x, \pi) = \prod_{i=1}^{l_y} p_\theta\big(y[i] \mid x, \pi, y[1{:}i{-}1]\big)$. We use $z_1, \ldots, z_n$ to denote intermediate thoughts, and $r_1, \ldots, r_k$ to denote self-reflections. A node in a search tree is written as $s = [x, z_{1:i}]$.

Input–Output (IO) prompting The LM is prompted with task instructions and/or few-shot IO pairs and directly produces the final output: $y \sim p_\theta(\cdot \mid x, \pi_{\mathrm{IO}})$.

Chain-of-Thought (CoT) To handle $x \mapsto y$, CoT [37] instructs the model to first generate a sequence of thoughts and then the answer: $z_i \sim p_\theta(\cdot \mid x, z_{1:i-1}), \quad y \sim p_\theta(\cdot \mid x, z_{1:n})$. In practice, $[z_{1:n}, y]$ is sampled as a single contiguous sequence.

Reflexion Reflexion [28] augments the prompt with episodic self-reflections $r_{1:k}$ from the previous k iterations. The agent then generates new solutions conditioned on the previous feedbacks: $y \sim p_\theta(\cdot \mid x, r_{1:k})$. Intuitively, r_i provides textual semantic gradient signals [28, 45], indicating common errors to avoid and corrective cues.



(a) An output example of M_r on programming task using HumanEval dataset.

(b) An output example of M_p on multi-hop QA task using HotpotQA dataset.

Figure 1: Illustration of the output produced by M_*

Diversity of Thoughts (DoT) DoT [19] enhances the diversity of reflection feedback by using explicit prompt-level instructions to generate a set of diversified reflections $\{r_i\}_{i=1}^k$, thereby reducing redundancy and improving coverage of solutions. The decoding objective remains: $y \sim p_\theta(\cdot \mid x, r_{1:k})$.

Tree-of-Thought (ToT) and LATS ToT [42]lifts CoT into a search over partial solutions $s = [x, z_{1:i}]$. New thoughts are proposed via CoT-style sampling $z_i \sim p_\theta(\cdot \mid x, z_{1:i-1})$, while DFS/BFS is used to explore the search tree. LATS [49] extends this view with Monte-Carlo Tree Search (MCTS) [7], repeatedly selecting, expanding, simulating, and backpropagating values over nodes s, thereby constructing high-value trajectories of thoughts leading to a more probable correct y.

3 Augmenting Language Agents with Parametric Knowledge

In this section, we show how `ParamAgent` leverages parametric knowledge to augment LLM-based agents. Depending on the domain, `ParamAgent` employs different forms of parametric knowledge. Speficically, **(1)** A reflection-oriented module M_r to synthesize model-based reflection for programming and math, and **(2)** A decomposition-oriented module M_p to produce semantic units for multi-hop QA. The detailed pseudo-code can be found in Appendix B, a shorter version can be found in Algorithm 1.

3.1 Global-Local Reflection

To incorporate cross-sample reflective signals beyond instance-specific cues, we propose a *global–local reflection* mechanism. The key idea is to combine self-reflections derived from episodic memory with global reflections synthesized by a parametric module M_r.

Training M_r. We obtain M_r by fine-tuning a pretrained LLM on a curated dataset where reflective feedback is provided as supervision. Through this process, the module internalizes population-level patterns into its model parameters, and learns to synthesize model-based reflections and corrective cues. We provide more details regarding the dataset curation and training in Appendix D.2. An example output from M_r is shown in Figure 1a.

Formulation. Having obtained M_r, `ParamAgent` conditions jointly on two sources of feedback:

$$y \sim p_\theta(\cdot \mid x, r_{1:k}, r_k^g), \quad r_k^g \sim p_\psi(\cdot \mid x), \tag{1}$$

where $r_{1:k}$ denotes k self-reflections collected across iterations, and r_k^g is the global reflection generated by M_r at the k-th iteration.

Usage. In each episode, M_r samples a global reflection r_k^g, which is injected into the prompt alongside self-reflections from the memory. A low sampling temperature is used in the first round to ensure informative feedback, while later rounds adopt a higher temperature to promote diversity. Importantly, r_k^g is used only as a transient input and is not stored in memory; the episodic memory only maintains self-reflections generated by the agent itself.

3.2 Semantic Decomposition

Beyond reflections, the parametric module can also generate structured knowledge. Inspired by *chunking* and the *working memory* model from cognitive science [23, 2], we introduce M_p to decompose complex multi-hop queries into compact semantic units that guide reasoning, one such example is illustrated in Figure 1b.

Training M_p. Similar to M_r, we fine-tune a pretrained LLM where semantic decompositions (e.g., entities, relations, constraints, answer types, etc.) serve as the training signal. Details are deferred in Appendix D.2.

Formulation. `ParamAgent` then conditions jointly on the original query x, the semantic units Z, and a set of self-reflections $r_{1:k}$ derived from prior attempts, with the final answer produced as:

$$y \sim p_\theta(\cdot \mid x, Z, r_{1:k}). \qquad (2)$$

Algorithm 1: Pseudocode for `ParamAgent`

Require: Dataset $\mathcal{D}$, base LM p_θ, parametric module M_* with params ψ, max iterations $T_{\max}$

$\mathcal{M} \leftarrow \emptyset$ ▷ Initialize memory
for $x \in \mathcal{D}$ **do**
  for $t = 1$ to $T_{\max}$ **do**
    $T \leftarrow \begin{cases} 0.2 & \text{if } t = 1 \\ 1.0 & \text{otherwise} \end{cases}$
    $G_{t-1} \sim p_\psi(\cdot \mid x; T)$ ▷ r_{t-1}^g **or** Z
    $r_{1:t-1} \leftarrow$ RETRIEVEREFLECTIONS$(\mathcal{M}, x)$
    $y_t \sim p_\theta(\cdot \mid x, r_{1:t-1}, G_{t-1})$
    if EVALUATE(y_t, x) **then**
      break
    else
      $r_t \leftarrow$ GENERATESELFREFLECTION(y_t)
      $\mathcal{M} \leftarrow \mathcal{M} \cup \{(x, r_t)\}$ ▷ **Store reflection**
    end if
  end for
end for

By combining self reflection with model-based semantic decomposition, the agent benefits from both local reflective feedback and global structural guidance.

Usage. Similarly, at the first round, M_p generates semantic units under a low temperature, and the temperature is increased in the remaining rounds to promote diversity.

3.3 Relation to Previous Studies

Global-local reflection Our design is inspired by Reflexion [28], which improves reasoning through iterative interaction between an actor M_a, an evaluator M_e, and a self-reflection module M_{sr}. The actor generates candidate outputs, the evaluator provides feedback based on task-specific signals, and the self-reflection module produces natural language feedback that is appended to the context of the next trial. In `ParamAgent`, we propose a new module M_r, which encodes cross-sample similarities into the model parameters, allowing the module to generate higher-quality reflections that facilitate the reasoning process of the language agent.

Semantic decomposition A key advantage of `ParamAgent` lies in its flexibility: the method can provide different forms of knowledge depending on the task. For multi-hop QA, we introduce semantic decomposition, which is conceptually related to CoT prompting. In standard CoT, intermediate thoughts z_i are elicited directly by the base LM. In contrast, our framework employs a dedicated parametric module M_p, which generates a structured set of intermediate thoughts Z that guide the reasoning process. Furthermore, we show that semantic decomposition can be seamlessly combined with reflection-based framework. Together they complement each other, yielding richer guidance to augment reasoning.

4 Experiments

In this section, we detail our experimental setup and present results across programming, math reasoning, and multi-hop QA. We then conduct more in-depth empirical analyses of our proposed method. More experimental results are included in Appendix D, including experiments with 70B scale LLMs.

4.1 Setup

Datasets We evaluate our framework across three domains. For programming, we use HumanEval [8] and MBPP [1]. For math reasoning, we adopt the MATH dataset [13], which covers competition-level problems of varying difficulty across seven subjects. For multi-hop QA, we use HotpotQA [41] and 2WikiMultiHopQA [14], which require reasoning across multiple passages. Further details about each dataset, as well as how we perform dataset splits are provided in later sections.

Evaluation For programming tasks, we follow prior work [28, 19] and report Pass@1. During generation, only visible or synthetic test cases are used, while final evaluation is conducted on hidden test cases; a score of 1 is assigned if all tests pass and 0 otherwise. For math reasoning and multi-hop QA, we report 0–1 accuracy on subsampled testsets.

Baselines We compare against: (1) **Base**, the underlying LLM agent without reflection; (2) **Reflexion** [28], which uses episodic self-reflections; (3) **DoT** [19], which augments Reflexion with prompt-level diversity. (4) **DoT-bank** [19], which further incorporate a memory bank to enrich the reflective feedbacks. **(5)** In addition, we develop a baseline that uses only the parametric module to generate reflections or semantic units, referred to as *model-based reflection* or *model-based CoT*. This baseline utilizes M_* purely as a parametric sampler, without performing self-reflection. The pseudocode can be found in Appendix B. Our full model `ParamAgent` incorporates both episodic memory and parametric memory for iterative reasoning, yielding stronger and more diverse feedback signals. Finally, we also explore an extended variant `ParamAgent-plus`, where we further introduce a memory bank similar to DoT. This extension allows the agent to combine episodic memory, parametric memory, and cross-sample memory, offering a comprehensive integration of different knowledge sources.

To ensure a comprehensive evaluation, we employ three backbone LLMs with varying levels of reasoning capability: (1) **Llama-3.1-8B** [11], a strong open-source reasoning model; (2) **Mistral-7B-v0.2** [18], a competitive medium-sized model with efficient inference; and (3) **Qwen2-1.5B-instruct** [3], a TogetherAI's hosted version of Qwen2 1.5B, fine-tuned into an instruction-following variant. This selection of backbones allows us to examine how our approach performs across different model sizes and reasoning strengths. We also provide results with stronger base LLMs in Appendix D.4, showing that even when the parametric module remains an 8B model, it can still provide noticable gains to agents built on 70B-scale LLMs.

Hyperparameters Across all experiments, we fix the number of reflection iterations to 5 for both baseline methods and our proposed approach. For `ParamAgent` and its variants, we set the sampling temperature to $T = 0.2$ during the first iteration, and $T = 1.0$ in the subsequent iterations to promote diversity. For LoRA finetuning of the parametric modules, we use a rank of $r = 128$, scaling factor $\alpha = 32$, a learning rate of $2e - 5$, and train for 3 epochs.

Parametric module The parametric module is designed to internalize population-level knowledge across tasks $t \in \mathcal{D}$. We first construct a dataset $\{(t_i, m_i)\}_{i=1}^{n}$ by prompting an LLM on synthetic data or a subset of the training set to enumerate failure modes or semantic units, where n is typically around 10^4. M_r or M_p is then obtained by finetuning a pretrained LLM using LoRA [16], encoding this knowledge into its parameters. In our experiments, we instantiate the module with Llama-3.1-8B. More details on the setup, dataset construction, training procedure, and implementation of the parametric module are deferred to Appendix D.2.

4.2 Programming

Datasets We evaluate our framework on two widely used programming benchmarks: HumanEval [8] and MBPP [1]. HumanEval consists of Python programming problems that test functional correctness using hidden unit tests, while MBPP covers beginner to intermediate-level Python problems designed for program synthesis.

Table 1: Performance on HumanEval and MBPP datasets. **Bold** denotes the best result, and <u>underline</u> marks the second best. ↑ and ↓ indicate the absolute improvement or decrease relative to the Base method. For clarity, the prompt token usage of the Base method is normalized to 1. Table 2 and Table 3 use the same notation, which we omit from the captions due to space constraints.

Dataset	Method	Llama-3.1-8B		Mistral-7B-v0.2		Qwen2-1.5B	
		Pass@1	#Prompt Tokens	Pass@1	#Prompt Tokens	Pass@1	#Prompt Tokens
HumanEval	Base	59.15	1.00	32.93	1.00	41.46	1.00
	Model-based Reflection	78.05 ↑18.90	9.15	**68.29** ↑35.36	23.73	**68.91** ↑27.45	6.77
	Reflexion	76.22 ↑17.07	9.29	51.22 ↑18.29	28.54	49.39 ↑7.93	18.30
	DoT	73.17 ↑14.02	17.45	46.95 ↑14.02	43.06	56.56 ↑15.10	15.26
	DoT-bank	<u>79.56</u> ↑20.41	24.71	54.26 ↑21.33	61.62	60.10 ↑18.64	31.28
	Ours	**82.93** ↑23.78	19.18	<u>67.07</u> ↑34.14	70.38	<u>66.46</u> ↑25.00	33.45
MBPP	Base	47.61	1.00	24.94	1.00	42.06	1.00
	Model-based Reflection	52.90 ↑5.29	31.93	<u>47.86</u> ↑22.92	20.98	52.89 ↑10.83	25.35
	Reflexion	58.69 ↑11.08	37.18	28.46 ↑3.52	14.02	47.61 ↑5.55	26.95
	DoT	61.21 ↑13.60	51.83	19.79 ↓5.15	25.45	47.37 ↑5.31	21.48
	DoT-bank	<u>64.82</u> ↑17.21	69.41	24.68 ↓0.26	60.09	<u>53.38</u> ↑11.32	60.95
	Ours	**67.00** ↑19.39	86.39	**51.64** ↑26.70	36.88	**54.90** ↑12.84	66.86

Table 2: Performance on MATH dataset.

Dataset	Method	Llama-3.1-8B		Mistral-7B-v0.2		Qwen2-1.5B	
		Acc	#Prompt Tokens	Acc	#Prompt Tokens	Acc	#Prompt Tokens
MATH	Base	48.20	1.00	12.23	1.00	8.99	1.00
	Model-based Reflection	45.81 ↓2.39	2.58	13.31 ↑1.08	2.82	16.91 ↑7.92	2.84
	Reflexion	58.99 ↑10.79	23.33	19.78 ↑7.55	27.67	21.94 ↑12.95	18.39
	DoT	64.38 ↑16.18	34.17	23.25 ↑11.02	40.51	22.30 ↑13.31	31.99
	DoT-bank	<u>73.02</u> ↑24.82	83.92	<u>35.61</u> ↑23.38	122.92	<u>24.37</u> ↑15.38	76.71
	`ParamAgent`	67.99 ↑19.79	57.01	28.06 ↑15.83	92.91	22.30 ↑13.31	70.07
	`ParamAgent-plus`	**75.45** ↑27.25	111.32	**38.96** ↑26.73	196.18	**25.97** ↑16.98	144.25

Results From Table 1, we can observe that: **(1)** Model-based Reflection, which relies solely on parametric reflection without using self-reflection, already achieves substantial gains or performs comparably to the baseline methods across different LLM backbones. This indicates that parametric knowledge alone can provide useful reflective signals, effectively guiding the agent toward higher-quality solutions. **(2)** Furthermore, `ParamAgent`, which integrates both instance-specific self-reflections and model-based parametric reflections, achieves consistent improvements across most datasets and base models. This highlights the complementary benefits of combining feedback at different granularities: local signals capturing trial-specific errors and global signals capturing population-level patterns. **(3)** Notably, although DoT-bank also leverages global-level reflective feedback, it underperforms compared to `ParamAgent` in most scenarios. This highlights that retrieval-based memory modules are less effective than model-based parametric modules in capturing deep relational patterns across tasks. **(4)** Finally, `ParamAgent` is also cost-effective, its token consumption is on par or lower than DoT-bank while delivering stronger performance.

4.3 Math Reasoning

Datasets For mathematical reasoning, we evaluate on the MATH dataset [13], which consists of competition-level problems spanning seven subjects: Prealgebra, Algebra, Number Theory, Counting and Probability, Geometry, Intermediate Algebra, and Precalculus. To construct our evaluation set, we randomly sample 40 problems from each subject in testset, ensuring that the problems cover diverse topics and allows us to comprehensively assess the performance of different methods across varying topics.

Results From Table 2, we can make several observations. **(1)** Compared with model-based reflection alone, instance-level self-reflection proves more effective for math reasoning. However, when model-based reflective feedback is incorporated, `ParamAgent` consistently improves over Reflexion across all 3 backbone LLMs, and outperforms DoT on all LLM backbones. **(2)** Furthermore, `ParamAgent-plus`, which incorporates all levels of memory modules, achieves state-of-the-art results across all 3 backbone LLMs. This clearly demonstrates the added value of parametric knowledge: by combining episodic memory, parametric memory, and cross-sample memory, the agent gains access to richer and more complementary feedback signals, enabling stronger performance on competition-level mathematical reasoning tasks.

Table 3: Performance on HotpotQA and 2WikiMultiHopQA datasets.

Dataset	Method	Llama-3.1-8B		Mistral-7B-v0.2		Qwen2-1.5B	
		Acc	#Prompt Tokens	Acc	#Prompt Tokens	Acc	#Prompt Tokens
HotpotQA	Base	57.67	1.00	45.00	1.00	43.66	1.00
	Model-based CoT	61.67 ↑4.00	1.46	54.33 ↑9.33	1.46	48.10 ↑4.44	1.44
	Reflexion	71.33 ↑13.66	4.13	62.33 ↑17.33	4.67	50.03 ↑6.37	6.22
	DoT	66.67 ↑9.00	7.10	58.33 ↑13.33	8.97	49.32 ↑5.66	58.05
	DoT-bank	<u>72.00</u> ↑14.33	13.28	<u>66.33</u> ↑21.33	19.35	<u>52.02</u> ↑8.36	109.54
	`ParamAgent`	**78.33** ↑20.66	22.25	**69.67** ↑24.67	34.99	**64.66** ↑21.00	14.69
2WikiMultiHopQA	Base	40.33	1.00	21.00	1.00	40.33	1.00
	Model-based CoT	54.67 ↑14.34	1.39	46.33 ↑25.33	1.21	40.66 ↑0.33	1.19
	Reflexion	78.67 ↑38.34	5.47	61.33 ↑40.33	5.86	<u>51.00</u> ↑10.67	6.56
	DoT	66.67 ↑26.34	7.03	52.13 ↑31.13	6.40	47.83 ↑7.50	30.55
	DoT-bank	<u>80.33</u> ↑40.00	12.49	<u>74.66</u> ↑53.66	8.10	50.49 ↑10.16	54.92
	`ParamAgent`	**88.67** ↑48.34	10.41	**81.33** ↑60.33	14.43	**63.33** ↑23.00	17.39

4.4 Multi-hop QA

Datasets We use a subset of samples from HotpotQA and 2WikiMultiHopQA for the evaluation. Specifically, for HotpotQA, from the training set, we randomly sample 100 examples for each difficulty level (easy, medium, and hard), resulting in 300 test samples. For 2WikiMultiHopQA, we focus on 4 representative categories: bridge comparison, comparison, compositional, and inference. We randomly draw 75 examples from each category, leading to a total of 300 test samples.

Results From Table 3, we can draw several conclusions. **(1)** Model-based CoT outperforms the Base method by a large margin across all three backbones. This indicates that decomposed semantics, when used as structured intermediate thoughts, facilitating the reasoning ability of the underlying LLM. **(2)** Although Model-based CoT underperforms compared to stronger baselines such as Reflexion and DoT-bank, `ParamAgent` achieves significant improvements over all state-of-the-art methods, even without incorporating a memory bank. This demonstrates the complementary advantages of semantic decomposition compared with reflective feedback, and highlights the effectiveness of combining them within a unified framework.

4.5 Additional Analysis

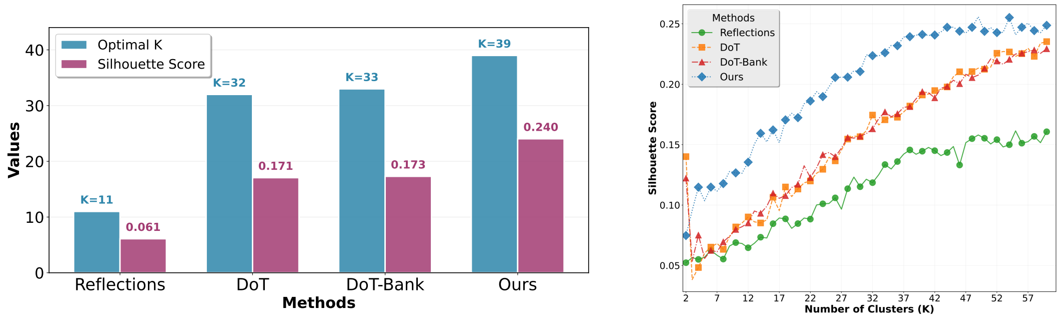
4.5.1 Quantifying the Diversity of Reflections

Setup We study to what extent the reflection trajectories produced by `ParamAgent` differ from those of other baselines. To this end, we maintain the complete reflection history for each sample and embed each reflection using the OpenAI `text-embedding-3-small` model. We focus on the HumanEval dataset for this analysis. Concretely, for N samples, and for each backbone LLM, we obtain a 2D tensor of shape $\mathbb{R}^{\sum_{i=1}^{N} n_i \times F}$, where n_i denotes the number of reflection iterations for sample i, and F is the embedding dimension. We then perform k-means clustering [21] over all reflections and apply the elbow method [30] to determine the optimal clustering number K^*. This provides a quantitative measure of the semantic diversity of reflective feedback across methods. Additionally, for each K, we compute the silhouette score to evaluate clustering quality.

Results As shown in Figure 2, `ParamAgent` achieves an optimal clustering number of $K^* = 39$, substantially larger than that of Reflexion, DoT and DoT-bank. This indicates that the reflective outputs of Reflexion lack diversity, whereas the parametric feedback of `ParamAgent` introduces significantly richer and more varied reflective signals. Moreover, across all clustering numbers K, the silhouette score of `ParamAgent` is consistently higher than those of competing methods. This suggests not only that `ParamAgent` generates more diverse reflections, but also that these reflections form more coherent semantic groups.

4.5.2 Effect of Reflection Format from M_r on Programming Tasks

Setup In this section, we conduct an ablation study on the content of the reflections produced by M_r for programming tasks. As introduced in Section 3, for a given programming task t, M_r samples two complementary components: (1) textual reflective feedback describing potential pitfalls, and (2) code snippets implementing possible buggy solutions to illustrate failure modes. To analyze their

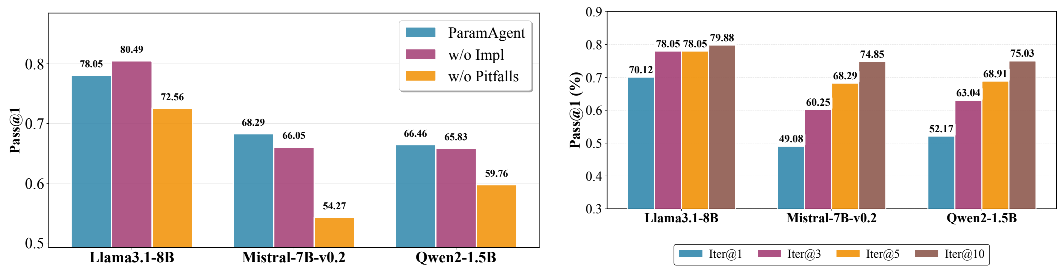


(a) Optimal clustering number K^* across methods and the corresponding Silhouette scores.

(b) Silhouette score for every clustering number $K \in [2, 60]$.

Figure 2: Quantitative analysis of reflection diversity: (a) optimal clustering number K^*; (b) silhouette scores for different K.

contributions, we post-process the outputs from M_r by removing one of the components. We then evaluate the resulting variants on the HumanEval dataset.



(a) Ablation study on the reflection format of M_r on programming task.

(b) Ablation study on iteration numbers of Model-based Reflection on programming task.

Figure 3: Ablation studies.

Results From Figure 3a, we can observe that: **(1)** The textual reflective feedback (w/o Impl) proves to be more important across different backbone LLMs. When only buggy code implementations are preserved without natural language descriptions, the performance sometimes even degrades, as observed in Llama-3.1-8B. **(2)** When only textual reflective feedback is kept, both Mistral-7B-v0.2 and Qwen2-1.5B show moderate drops in accuracy. This suggests that including buggy code implementations also provides useful complementary signals. Overall, these results indicate that outputting both natural language reflections and buggy code examples is a robust design choice.

4.5.3 Effect of Iteration Number on Model-based Reflection

Setup In the main experiments, we fixed of iterations to 5 for fairness. Here we vary the iteration count of Model-based Reflection in $\{1, 3, 10\}$ to examine how diversity affect the model performance.

Results As shown in Figure 3b, running only a single iteration yields subpar performance, indicating that providing one informative reflection ($T = 0.2$) is insufficient. Performance improves steadily as the iteration number increases significantly, even without an episodic memory buffer. This highlights that the diversity introduced by the parametric memory is crucial and effective for performance gains.

4.5.4 Effect of Auxiliary Datasets

Setup In our experiments, we use GPT-4o-mini to construct auxiliary datasets containing reflective signals and semantic units. To isolate the influence of using a stronger LLM during supervision generation, we additionally employ Llama3.1-8B to produce the same supervision and evaluate its impact on the parametric module. We conduct assessments on both the HumanEval and HotpotQA benchmarks.

Results As shown in Table 4, we observe two key findings. (1) relative to GPT-4o-mini, ParamAgent exhibits a performance drop when supervised with Llama3.1-8B. This is due to the supervision generated by a more capable LLM (e.g., reflective signals) is generally more accurate.

(2) Despite this drop, our method still surpasses other state-of-the-art baselines by a substantial margin. These results highlight two important conclusions: (1) the parametric memory provides additional diversity to the reflective process, which in turn enhances the agent's reasoning capability; and (2) higher-quality auxiliary datasets can further improve the parametric module, particularly benefiting smaller models.

Table 4: Performance on HumanEval and HotpotQA with Llama-3.1-8B generated synthetic datasets.

Method	HumanEval Pass@1	HotpotQA Acc
Base	59.15	57.67
Model-based Reflection / CoT	78.05 ↑18.90	61.67 ↑4.00
Reflexion	76.22 ↑17.07	71.33 ↑13.66
DoT	73.17 ↑14.02	66.67 ↑9.00
DoT-bank	79.56 ↑20.41	72.00 ↑14.33
`ParamAgent`	78.05 ↑18.90	76.33 ↑18.66
`ParamAgent-plus`	**86.59** ↑27.44	**83.33** ↑25.66
`ParamAgent`	82.93 ↑23.78	78.33 ↑20.66

5 Related Work

We discuss the most relevant work below, with additional related work in Appendix A.

LLM Reasoning LLMs have demonstrated emergent abilities to perform multi-step reasoning when prompted appropriately. for instance, CoT prompting elicits the model to generate explicit intermediate reasoning steps and significantly improves performance on complex tasks [37]. Self-Consistency [35] further improves CoT by sampling multiple reasoning paths and aggregating them via majority voting, which increases robustness. ReAct [43] is a seminal approach that interleaves reasoning steps with actions (e.g., tool uses or environment queries) in an interactive decision-making loop, allowing the model to both "think" and "act" step-by-step. Other methods focus on iterative self-feedback, highlighting that reasoning is a process, not a one-shot [22, 28]. `ParamAgent` follows this iterative reasoning paradigm but avoids sophisticated search procedures.

External Memory in LLMs Memory has become central for agents tackling multi-step reasoning [47]. Short-term mechanisms such as Self-Refine [22] use the model's own recent outputs as transient memory for iterative refinement, while Reflexion [28] maintains episodic logs of errors and reflections to guide retries within a task. These approaches however, reset once a new problem begins. To address this limitation, external memory has been proposed to augment agentic reasoning [5, 27, 34, 27, 48, 36, 17, 40, 9, 19]. These methods mainly rely on non-parametric memory, either through textual logs or retrieval databases. By contrast, `ParamAgent` introduces a external parametric memory module M_*, which retrieves the knowledge from model-based sampler rather than recalling raw traces, enabling it to generate population-level knowledge that can be adapted to different domains.

6 Conclusions

We propose `ParamAgent`, a language agent framework that introduces a parametric module to move beyond instance-level reflection. By encoding cross-sample regularities into model parameters, `ParamAgent` internalizes global patterns and synthesizes population-level insights in a generative manner. Across programming, mathematical reasoning, and multi-hop QA, `ParamAgent` delivers substantial performance gains over state-of-the-art baselines while maintaining cost-effectiveness, highlighting the potential of parametric memory as a plug-in module for building language agents.

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Appendix

Contents

A Additional Related Work

Diversity in LLM Reasoning A key challenge in multi-step reasoning is avoiding redundant or myopic thought patterns. Recent works therefore encourage diversity of reasoning paths. One simple but effective approach is self-consistency decoding [35], which samples multiple independent chains-of-thought and then selects the final answer by majority vote. Beyond this, researchers have proposed methods to actively inject diversity into the reasoning process. For example, prompting the model with different personas or perspectives (e.g. "Think like a mathematician" vs. "Explain as a teacher") can yield varied solution paths [24]. Another line of work trains LLMs to generate diverse solutions through specialized learning algorithms: Flow of Reasoning framework [44] the generation of reasoning steps as a search problem and uses a GFlowNet-based [4] fine-tuning to stochastically sample multiple high-reward reasoning trajectories, achieving greater coverage of the solution space. The recent DoT framework [19] explicitly tackles the lack of exploration by producing non-redundant self-reflections to ensure each iteration explores new solution paths, rather than repeating past failures. Empirically, DoT shows that encouraging such diversity yields substantial gains on challenging reasoning tasks. `ParamAgent` adopts the principle of diversification in a notably simple way: by drawing each new reasoning attempt from a high-temperature parametric sampler (the memory module). This high-temperature sampling from the learned model-based memory introduces stochasticity that is easy to implement yet effective at covering different problem-solving trajectories, without needing elaborate persona prompts or complex search procedure.

Parametric Memory in LLM Reasoning Compared with textual memory, parametric memory remains under-explored in LLM agents. While textual stores dominate due to interpretability and ease of use, recent studies have also explored encoding memory directly into model parameters, thereby avoiding the length limitations of textual memory. Character-LLM [26] fine-tunes role-playing agents with character experiences to faithfully simulate personas. HuaTuo [33] tunes LLaMA [31] with Chinese medical knowledge to enhance clinical QA and instruction following. DoctorGLM [39] develops a Chinese medical dialogue system, demonstrating that physician-style models can be obtained with moderate fine-tuning cost. Radiology-GPT [20] instruction-tunes on radiology corpora to outperform general LLMs on imaging-focused tasks. These approaches directly fine-tune the base LLM, yielding specialized models tailored to particular domains. By contrast, our framework keeps the base agent intact and fine-tunes an external parametric module that generates domain-specific reflective cues or semantic decompositions. This modular design allows the parametric module to serve as a plug-in component for different agents, while reducing the risk of catastrophic forgetting in the backbone. A detailed justification of this external design choice is provided in Appendix C. More details on parametric memory in agentic reasoning can be found in [47].

Cognitive Science Inspirations for Reasoning Cognitive science research shows that people manage complexity by chunking information into structured units, thereby reducing cognitive load and effectively increasing capacity for multi-step reasoning [23]. Classic working memory models further posit a central executive that maintains and manipulates only a small set of active items, motivating reasoning procedures that keep a compact buffer of intermediate results [2]. In parallel, problem solving is often modeled as hierarchical decomposition, where a complex goal is resolved by recursively addressing sub-goals and recombining their solutions [29]. These insights motivate semantic decomposition in multi-hop QA: parse a query into compact units (e.g., entities, relations, constraints, answer type) and an explicit sequence of inference steps; solve sub-queries sequentially while maintaining a small active buffer of intermediates; then integrate the chunks to produce the final answer.

B Pseudocodes for `ParamAgent`

In this section, we present pseudocode for `ParamAgent` in Algorithm 2. We also include pseudocodes for Model-based Reflection and Model-based CoT in Algorithm 3 and `ParamAgent-plus` in Algorithm 4 for clarity.

C Rationale for External Module Fine-Tuning

We justify our choice to fine-tune an external parametric module rather than the base language agent.

Training objectives Given an input x, the external module is trained to produce either a reflection r or semantic units $Z = \{z_i\}_{i=1}^{m}$:

$$\max_{\psi} \ \mathbb{E}_{(x,r)\sim\mathcal{D}_r}[\log p_\psi(r \mid x)], \qquad \max_{\psi} \ \mathbb{E}_{(x,Z)\sim\mathcal{D}_Z}[\log p_\psi(Z \mid x)]. \tag{3}$$

At inference, the agent conditions on $r_k^g \sim p_\psi(\cdot \mid x)$ or on $Z \sim p_\psi(\cdot \mid x)$:

$$y \sim p_\theta(\cdot \mid x, r_{1:k}, r_k^g), \qquad y \sim p_\theta(\cdot \mid x, Z, r_{1:k}). \tag{4}$$

Why not fine-tune the agent directly? Directly fine-tuning the base LLM within the agent introduces the following challenges:

(1) Distribution mismatch. In practice, an agent generates reflections autoregressively as $p_\theta(r_k \mid x, r_{1:k-1})$. If we fine-tune the base model only on $p_\theta(r \mid x)$ without its own history, the training distribution no longer matches the inference distribution $p_\theta(r_k \mid x, r_{1:k-1})$. Bridging this gap would require sequence-level supervision and far more data due to the more complex distribution form.

(2) Capability interference. The agent must also maintain $p_\theta(y \mid x, r_{1:k})$ to act (e.g., generate code or multi-hop answers). Pushing the same parameters toward a specialized model for reflection generation can interfere with this objective, degrading the agent's general problem-solving ability.

Benefits of using external module In the meantime, adopt an external LLM module for parametric knowledge introduces several advantages:

(1) Simpler supervision. Decoupling the base LLM and the external LLM model yields a simpler objective $p_\psi(r \mid x)$ or $p_\psi(Z \mid x)$ rather than the history-conditioned $p_\theta(r_k \mid x, r_{1:k-1})$, reducing modeling complexity and data requirements.

(2) Modular knowledge forms. The module can emit different forms of parametric knowledge (e.g., reflections r for programming/math via M_r, semantic units Z for multi-hop QA via M_p), complementing episodic self-reflection $r_{1:k}$ without altering the base agent.

(3) Stability and reuse. Keeping the base LLM in the agent fixed also avoids interference with $p_\theta(y \mid x, r_{1:k})$, mitigates catastrophic forgetting, and enables plug-in use across agents and backbones.

Algorithm 2 `ParamAgent`

Require: Dataset $\mathcal{D}$, Base LM p_θ, Parametric Module M_* with parameters ψ, Max iterations $T_{\max}$, Pass@k K
Ensure: Solutions for each task
Initialize: Episodic memory $\mathcal{M} \leftarrow \emptyset$
for each task $x \in \mathcal{D}$ **do**
  solved $\leftarrow$ False, $k \leftarrow 0$
  while $k < K$ **and not** solved **do**
    $t \leftarrow 1$, $y_{\text{curr}} \leftarrow$ None
    while $t \leq T_{\max}$ **and not** solved **do**
      # Generate parametric insights for iteration t
      if $t = 1$ **then**
        $T \leftarrow 0.2$ ▷ informative first-round sampling
      else
        $T \leftarrow 1.0$ ▷ promote diversity thereafter
      end if
      if *task is coding/math* **then**
        $r^g_{t-1} \sim p_\psi(\cdot \mid x; T)$ ▷ global reflection from M_r
      else ▷ multi-hop QA
        $Z \sim p_\psi(\cdot \mid x; T)$ ▷ semantic units from M_p
      end if
      # Combine parametric and episodic knowledge
      $r_{1:t-1} \leftarrow$ RETRIEVEREFLECTIONS$(\mathcal{M}, x)$ ▷ local (self) reflections up to $t-1$
      if *task is coding/math* **then**
        $y_{\text{curr}} \sim p_\theta(\cdot \mid x, r_{1:t-1}, r^g_{t-1})$ ▷ global–local fusion
      else
        $y_{\text{curr}} \sim p_\theta(\cdot \mid x, Z, r_{1:t-1})$ ▷ semantic decomposition
      end if
      # Evaluate and update episodic memory
      (passed, feedback) $\leftarrow$ EVALUATE(y_{curr}, x)
      if passed **then**
        solved $\leftarrow$ True
      else
        $r_t \leftarrow$ GENERATESELFREFLECTION$(y_{\text{curr}}$, feedback$)$
        $\mathcal{M} \leftarrow \mathcal{M} \cup \{(x, r_t)\}$ ▷ store only self-reflections
      end if
      $t \leftarrow t + 1$
    end while
    $k \leftarrow k + 1$
  end while
end for

In conclusion, fine-tuning an external module rather than the base LLM offers a simpler training objective, preserves the general capabilities of the agent, and enables flexible plug-in usage across domains and backbones, which justifies this design choice.

D More Experimental Details Results

D.1 Dataset Statistics

Programming. For programming tasks, we evaluate on HumanEval [8] and MBPP [1]. HumanEval consists of 164 hand-written Python programming problems, each accompanied by hidden unit tests and a small number of visible test cases. We additionally consider MBPP, which provides 974 crowd-sourced Python problems; following prior work, we use the 397 problems from the filtered evaluation split.

Algorithm 3 Model-based Reflection (CoT)

Require: Dataset $\mathcal{D}$, Base LM p_θ, Parametric Module M_* with parameters ψ, Max iterations $T_{\max}$, Pass@k K

Ensure: Solutions for each task

```
for each task x ∈ D do
    solved ← False, k ← 0
    while k < K and not solved do
        t ← 1
        while t ≤ T_max and not solved do
            # Parametric guidance only (no episodic memory)
            T ← { 0.2  if t = 1
                { 1.0  otherwise
            if task is coding/math then
                r^g_{t-1} ~ p_ψ(· | x; T)          ▷ global reflection from M_r
                y_t ~ p_θ(· | x, r^g_{t-1})
            else                                   ▷ multi-hop QA
                Z ~ p_ψ(· | x; T)                  ▷ semantic units from M_p
                y_t ~ p_θ(· | x, Z)
            end if
            # Evaluate (no memory write)
            passed ← EVALUATE(y_t, x)
            if passed then
                solved ← True
            end if
            t ← t + 1
        end while
        k ← k + 1
    end while
end for
```

Math. For mathematical reasoning, we adopt the MATH dataset [13], which contains competition-style math problems spanning seven subjects including Algebra, Geometry, Number Theory, Counting and Probability, and Precalculus. We randomly sample a balanced subset across categories for evaluation.

Multi-hop QA. For multi-hop question answering, we use HotpotQA [41] and 2WikiMultiHopQA [14]. In HotpotQA, we stratify by difficulty level and randomly sample 100 examples from each category (easy, medium, hard), yielding a total of 300 evaluation samples. For 2WikiMultiHopQA, we stratify by question type and randomly sample 75 examples from each of four categories (bridge comparison, comparison, compositional, inference), again yielding 300 samples in total. These stratified subsets ensure balanced evaluation across different reasoning styles.

Table 5: Datasets used for Programming, Math, and Multi-hop QA tasks.

Task Type	Dataset Name	Size	Metric
Programming	HumanEval	164 problems, ∼3 visible test cases/problem	Pass@1
Programming	MBPP	397 sampled problems	Pass@1
Math	MATH	278 sampled problems across 7 subjects	0-1 Acc
Multi-hop QA	HotpotQA	300 sampled problems (100 per difficulty)	0-1 Acc
Multi-hop QA	2WikiMultiHopQA	300 sampled problems (75 per type)	0-1 Acc

D.2 Finetuning the Parametric Module

Programming For programming tasks, we curate a dataset by sampling 4000 coding problems from the APP dataset [12] at introductory level. In addition, we synthesize 4200 problems using GPT-4o-mini, covering a diverse range of programming domains. The code templates and prompt

Algorithm 4 `ParamAgent-plus`

Require: Dataset $\mathcal{D}$, Base LM p_θ, Parametric Module M_*, Max iterations $T_{\max}$
Init: Episodic memory $\mathcal{M} \leftarrow \emptyset$, Memory bank $\mathcal{B} \leftarrow \emptyset$, Failed $\mathcal{F} \leftarrow \emptyset$
Phase 1: Standard solving with memory banking
for each task $x \in \mathcal{D}$ **do**
  for $t = 1$ to $T_{\max}$ **or until solved do**
    $r^g_{t-1} \sim p_\psi(\cdot \mid x)$ with $T = 0.2$ if $t = 1$ else $T = 1.0$ ▷ Parametric insight
    $r_{1:t-1} \leftarrow$ Retrieve$(\mathcal{M}, x)$; $y \sim p_\theta(\cdot \mid x, r_{1:t-1}, r^g_{t-1})$
    if Evaluate(y, x) passes **then**
      Store (x, y, r^g_{t-1}) in $\mathcal{B}$; mark solved; **break**
    else
      $r_t \leftarrow$ Reflect(y); $\mathcal{M} \leftarrow \mathcal{M} \cup \{(x, r_t)\}$ ▷ Update episodic
    end if
  end for
  if not solved **then** $\mathcal{F} \leftarrow \mathcal{F} \cup \{x\}$
  end if
end for
Phase 2: Memory-augmented reattempt
for each $x \in \mathcal{F}$ **do**
  $\mathcal{T} \leftarrow$ RetrieveTopK$(\mathcal{B}, x)$; $x_{\text{aug}} \leftarrow$ Augment$(x, \mathcal{T})$
  for $t = 1$ to $T_{\max}$ **or until solved do**
    $r^g_{t-1} \leftarrow$ Extract$(\mathcal{T})$ **or** $p_\psi(\cdot \mid x_{\text{aug}})$ ▷ Reuse or generate (same T rule as above)
    $r_{1:t-1} \leftarrow$ Retrieve$(\mathcal{M}, x)$ + RetrieveByReflection$(\mathcal{B})$
    $y \sim p_\theta(\cdot \mid x_{\text{aug}}, r_{1:t-1}, r^g_{t-1})$; Evaluate and update $\mathcal{M}$, $\mathcal{B}$
  end for
end for

used for data generation are provided in Figure 4. For each problem, GPT-4o-mini is further asked to produce potential mistakes along with buggy implementations. This yields a dataset of reflective signals and corresponding erroneous code examples. We then finetune LLaMA-3.1-8B with LoRA on this dataset to obtain the programming-specific parametric module M_r.

Math For mathematical reasoning, we leverage the MATH training set [13]. From each subject area, we randomly sample 800 problems and adopt the same pipeline as in programming: GPT-4o-mini is prompted to produce reflective feedback and buggy derivations for each sampled problem. The resulting dataset is used to LoRA-finetune LLaMA-3.1-8B to instantiate M_r for math reasoning.

Multi-hop QA For multi-hop QA, we randomly sample 10000 instances from the HotpotQA [41] and 2WikiMultiHopQA [14] training sets respectively. GPT-4o-mini is prompted to output structured semantic units (e.g., entities, relations, constraints, answer types, and sub-questions) for each example. We then apply LoRA finetuning to LLaMA-3.1-8B on this dataset to build the parametric module M_p.

Across all domains, during dataset construction we provide one carefully designed demonstration example in the prompt to GPT-4o-mini. This ensures that the generated outputs (reflective feedback, buggy code, or semantic units) adhere to the required format, making the synthetic supervision more reliable.

D.3 More Implementation Details

We use the TogetherAI API service[1] to access all backbone models in our experiments. Specifically, we call the following model identifiers in implementation:

- `meta-llama/Meta-Llama-3.1-8B-Instruct-Turbo`
- `mistralai/Mistral-7B-Instruct-v0.2`

[1]`https://www.together.ai`

```
CATEGORIES = [
    # Core Text & Parsing
    "String Manipulation",
    "Regular Expression Parsing",
    "Natural-Language Tokenisation",
    "CSV / JSON Parsing",
    "URL / URI Parsing",
    "Text Justification / Word-Wrapping",
    # Lists, Arrays, SEQ
    "Array / List Algorithms",
    "Two-Pointer / Sliding-Window",
    "Sorting & Searching",
    "Statistical Summary of Sequences",
    # Maths & Numbers
    "Elementary Arithmetic / Algebra",
    "Number Theory & Divisibility",
    "Bitwise Operations",
    "Combinatorics & Counting",
    "Probability / Statistics",
    # Data-Structures
    "Hash / Set / Dict Operations",
    "Stack / Queue Simulation",
    "Linked-List Manipulation",
    "Matrix Operations",
    "Heap / Priority Queue Operations",
    "Trie / Prefix-Tree",
    # Graphs & Trees
    "Graph / Tree Traversal",
    "Binary Search Trees",
    "Dynamic Programming",
    "Recursion / Backtracking",
    "Union-Find / Disjoint Set",
    # Geometry / Coordinates
    "Geometry & Coordinate Computation",
    # Dates / Times / Calendars
    "Date & Time Calculations",
    # Miscellaneous Practical
    "File & Path Utilities",
    "Data-Type Conversion & Formatting",
    "Cipher / Encoding",
    "Simulation / Game Logic",
    "Misc Small-Scale Algorithms"
]
```

Figure 4: Schema of categories for synthesizing programming tasks used in our parametric module construction.

- `arize-ai/qwen-2-1.5b-instruct`

In Section D.4, we use 70B scale LLMs in our framework, the model identifiers are:

- `meta-llama/Meta-Llama-3.1-70B-Instruct-Turbo`
- `Qwen/Qwen2.5-72B-Instruct-Turbo`

All experiments are implemented in PyTorch [25].

D.4 How does `ParamAgent` perform with stronger base LLMs?

We further study the performance of `ParamAgent` when paired with stronger base models of around 70B parameters. Specifically, we use Llama-3.1-70B and Qwen2.5-72B-Instruct as the underlying LLMs, while keeping the parametric module fixed as Llama-3.1-8B. We evaluate on HumanEval

```
system_content = (
    "You are an expert Python engineer crafting coding problems.\n"
    "Follow this EXACT format:\n\n<template_example>\n\n"
    "- Randomly pick ONE category from the list above.\n"
    "- Output EXACTLY two lines:\n"
    "    func_sign: <signature with colon>\n"
    "    docstring: '<single-quoted string with \\n escapes>'\n"
    "- Do NOT wrap in JSON or triple quotes.\n"
    "- Avoid any collisions with past tasks.\n\n"
)
```

Figure 5: Prompt for synthesizing programming tasks

Table 6: Performance on HumanEval. **Bold** denotes the best result, and <u>underline</u> marks the second best. ↑ and ↓ indicate absolute change relative to the Base method. For clarity, the prompt token usage of the Base method is normalized to 1.

Dataset	Method	Llama-3.1-70B-Instruct		Qwen2.5-72B-Instruct	
		Pass@1	#Prompt Tokens	Pass@1	#Prompt Tokens
HumanEval	Base	80.49	1.00	82.92	1.00
	Model-based Reflection	87.80 ↑7.31	6.39	89.64 ↑6.72	3.48
	Reflexion	90.24 ↑9.75	4.31	88.41 ↑5.49	3.48
	DoT	90.85 ↑10.36	7.51	87.80 ↑4.88	6.05
	DoT-bank	<u>92.68</u> ↑12.19	9.14	90.24 ↑7.32	8.17
	`ParamAgent`	92.07 ↑11.58	11.90	<u>93.90</u> ↑10.98	8.93
	`ParamAgent-plus`	**95.03** ↑14.54	19.47	**95.12** ↑12.20	16.81

for programming and HotpotQA for multi-hop QA. The results are reported in Table 6 and Table 7 respectively.

Results. Across tasks, `ParamAgent` achieves performance that is on par with, or even surpasses, state-of-the-art baselines. Moreover, `ParamAgent-plus` consistently outperforms the best baseline methods by a large margin, highlighting the effectiveness of the parametric module. It is worth noting that our parametric module itself is only an 8B model, yet it integrates effectively with base LLMs as large as 70B. This demonstrates the strong potential of our approach when scaled further.

Table 7: Performance on HotpotQA dataset. **Bold** denotes the best result, and <u>underline</u> marks the second best. ↑ and ↓ indicate the absolute improvement or decrease relative to the Base method. For clarity, the prompt token usage of the Base method is normalized to 1.

Dataset	Method	Llama-3.1-70B-Instruct		Qwen2.5-72B-Instruct	
		Acc	#Prompt Tokens	Acc	#Prompt Tokens
HotpotQA	Base	70.00	1.00	73.33	1.00
	Model-based CoT	73.67 ↑3.67	1.43	74.10 ↑1.05	1.44
	Reflexion	82.33 ↑12.33	3.02	<u>82.67</u> ↑9.34	2.81
	DoT	73.67 ↑3.67	3.43	80.67 ↑7.34	4.30
	DoT-bank	80.00 ↑10.00	5.24	82.33 ↑9.00	7.87
	`ParamAgent`	<u>84.00</u> ↑14.00	7.70	81.00 ↑7.67	7.90
	`ParamAgent-plus`	**89.67** ↑19.67	13.69	**84.67** ↑11.34	15.43

D.5 Cost Analysis

Table 8 reports prompt/completion tokens and costs using Llama-3.1-8B. Costs are computed with TogetherAI pricing as of Aug 20, 2025 ($0.18 per million tokens). We can see that Model-based Reflection (CoT) is highly efficient, achieving strong accuracy with far fewer tokens than reflection-heavy methods like DoT-bank. By contrast, `ParamAgent` delivers the best results on both HumanEval and HotpotQA, at higher but still moderate cost, this highlights the advantages of incorporating various forms of memory modules.

Table 8: Token usage and cost on HumanEval and HotpotQA datasets with Llama3.1-8B as backbone LLM. Best and second-best metrics are in **bold** and <u>underline</u> respectively.

Method	HumanEval				HotpotQA			
	#Prompt Tokens	#Completion Tokens	Total Cost ($)	Pass@1 (%)	#Prompt Tokens	#Completion Tokens	Total Cost ($)	Acc (%)
Base	37,463	13,506	0.00917	59.15	164,013	1,801	0.02985	57.67
Model-based Reflection	342,805	82,280	0.07652	78.05	236,548	1,212	0.04280	61.67
Reflexion	348,068	73,538	0.07589	76.22	703,192	68,612	0.13892	71.33
DoT	653,981	169,986	0.14831	72.56	1,164,812	106,806	0.22889	66.67
DoT-bank	926,047	233,016	0.20863	<u>79.88</u>	2,179,148	195,283	0.42740	<u>72.00</u>
`ParamAgent`	814,627	163,257	0.17602	**82.93**	3,649,598	128,010	0.67997	**78.33**

D.6 A Case Study

We present a case study from the MBPP dataset, where both Reflexion and DoT fail to generate the correct implementation, while `ParamAgent` succeeds. To better understand this difference, we analyze the reflective history of all three methods and highlight the gists, as illustrated in Figure 6.

From the analysis, we observe that Reflexion and DoT often produce unhelpful sometimes even misleading reflections, which push the agent further away from the correct solution. In contrast, `ParamAgent` generates fewer such misleading reflections. We hypothesize that this advantage arises from the parametric knowledge encoded in M_r, which helps `ParamAgent` avoid unhelpful or error-prone reflective signals.

D.7 Prompt Templates

We provide prompt templates used in `ParamAgent` across different domains. The 1-shot reflective example for programming tasks can be found in Figure 7, and the corresponding math reasoning template in Figure 8. For multi-hop QA, the semantic decomposition 1-shot example is shown in Figure 9.

Instruction templates for generating actions for the programming is shown in Figure 10, the math reasoning instruction in Figure 11, and the multi-hop QA instruction in Figure 12.

Reflexion.
Problem: "The implementation failed the test case where it tries to return a single element that is not a list. This issue arises because the ^ operator in the set difference operation returns a set, and then we explicitly convert it to a list..."
Problem: "The implementation failed the test where it is expected to find a difference in the lists because the list to check for difference is a subset of the original list... This would return the union of the two lists, not the actual difference."
Problem: "The implementation failed the test where the difference should be a single element because it uses the symmetric difference operation which is not what's intended here... When converting the set back to a list using the list function, the order of elements is lost."
Problem: "When converting the set back to a list using the list function, the order of elements is lost."

DoT.
Problem: "The implementation failed the test due to a mismatch in the type of the function return value and the expected output."
Problem: "The function implementation does not handle the case where the input lists are not of the same length or contain duplicate elements."
Problem: "The function implementation does not correctly calculate the symmetric difference between two lists."
Problem: "The implementation failed due to a mismatch in the type of the function return value and the expected output, but the proposed fix in the previous reflection is incomplete."
Problem: "The function implementation does not correctly handle the case where the input lists are not of the same length or contain duplicate elements..."
Problem: "The function implementation does not correctly remove duplicates from the input lists, leading to incorrect results."

`ParamAgent`.
Problem: "The function implementation does not handle the case of empty lists correctly."
Fix: "Add a check at the beginning of the function to return an empty list if either of the input lists is empty..."
Problem: "The function implementation does not preserve the original order of elements in the lists." **Fix:** "Instead of using set operations..., use a list comprehension to create the difference list..."
Problem: "The function implementation does not handle non-integer values in the lists correctly."
Fix: "Add a check at the beginning... ensure that both input lists are lists of integers..."
Problem: "The function implementation does not handle non-list types correctly." **Fix:** "Add a check... ensure that both input arguments are lists..."
Problem: "The function implementation does not handle duplicates correctly." **Fix:** "Use a list comprehension... and preserve the original order..."
Problem: "The function implementation does not handle the case where the lists are identical."
Fix: "Return an empty list if the two input lists are identical."

Figure 6: Selected reflections on the `mbpp_769_Diff` problem. **Red** = critical errors that directly invalidate the implementation; **Orange** = conceptual pitfalls or misleading reasoning patterns; **Green** = key insights leading to a working solution; **Gray** = background noise (irrelevant or stylistic).

```
[Function Signature]:
def has_close_elements(numbers: List[float], threshold: float) -> bool:
    """Check if any two numbers in the list are closer than the threshold."""

[Potential mistakes]:
1. **Empty or Single-Element Lists** must return ‘False‘, not ‘True‘.
2. **Duplicate Values** must be compared (difference 0), so never drop duplicates.
3. Always use **absolute difference** (‘abs(a - b)‘), not raw subtraction.
4. Use the correct **strictness** (‘< threshold‘, not ‘<=‘).
5. Ensure you d o n t **exit too early**  check  all distinct pairs.

[Flawed Implementations Illustrating Each Pitfall]:

def has_close_elements_v1(numbers: List[float], threshold: float) -> bool:
    # BUG: returns True for empty or single-element lists
    if len(numbers) < 2:
        return True
    for i in range(len(numbers)-1):
        for j in range(i+1, len(numbers)):
            if abs(numbers[i] - numbers[j]) < threshold:
                return True
    return False

def has_close_elements_v2(numbers: List[float], threshold: float) -> bool:
    # BUG: removes duplicates, so identical values never compared
    numbers = sorted(set(numbers))
    for i in range(len(numbers)-1):
        if abs(numbers[i+1] - numbers[i]) < threshold:
            return True
    return False

def has_close_elements_v3(numbers: List[float], threshold: float) -> bool:
    # BUG: uses raw subtraction instead of abs()
    for i in range(len(numbers)-1):
        for j in range(i+1, len(numbers)):
            if (numbers[i] - numbers[j]) < threshold:
                return True
    return False

def has_close_elements_v4(numbers: List[float], threshold: float) -> bool:
    # BUG: uses <= instead of <, misclassifies exactly-threshold pairs
    for i in range(len(numbers)-1):
        for j in range(i+1, len(numbers)):
            if abs(numbers[i] - numbers[j]) <= threshold:
                return True
    return False

def has_close_elements_v5(numbers: List[float], threshold: float) -> bool:
    # BUG: breaks out of outer loop too soon
    ... (omit due to limited page)

END OF EXAMPLE
```

Figure 7: 1-shot example for reflective dataset construction for programming task.

Question. Circle O is located on the coordinate plane with center at $(2, 3)$. One endpoint of a diameter is at $(-1, -1)$. What are the coordinates of the other endpoint of this diameter? Express your answer as an ordered pair.

Pitfalls & Potential Mistakes

1. **Confusing the center with an endpoint.** Assuming the center is an endpoint leads to an incorrect reflection point.
2. **Incorrect use of the midpoint formula.** Forgetting that the center is the midpoint of the diameter, or solving $(x + x_2)/2 = \text{center}_x$ incorrectly.
3. **Using the wrong coordinates for the midpoint.** Plugging endpoint coordinates in place of the center (or vice versa) yields the wrong unknowns.
4. **Arithmetic errors.** Sign or algebra mistakes when solving, e.g. $2 = (-1 + x)/2 \Rightarrow x = 3$ (incorrect) instead of $x = 5$.
5. **Switching x and y.** Mixing x- and y-midpoint formulas, or using x values to solve for y.
6. **Incorrect interpretation of the diameter.** Thinking the diameter extends in the same direction from the center; doubling the vector or reflecting in the wrong direction.

Figure 8: 1-shot example for reflective dataset construction in math reasoning.

Example 1
Question. Anatoly Maltsev and Valentin Turchin were both from Russia, which of the two is known for his work as a mathematician?

Question Parsing and Intent Extraction

Key Components

- **Entity A:** Anatoly Maltsev — mathematician/logician; contributions in mathematical logic and abstract algebra.
- **Entity B:** Valentin Turchin — computer scientist/philosopher; work in cybernetics and philosophy of science.
- **Implied Relationship:** Comparative inquiry: which individual is more closely associated with mathematics.
- **Answer Type Expected:** Person name (e.g., “Anatoly Maltsev”).
- **Reasoning Type:** Comparative factual reasoning.
- **Required Background:** Biographical profiles or retrieved professional records.

Inference Trace

1. Retrieve factual data about Maltsev’s and Turchin’s primary academic domains.
2. Classify Maltsev as a mathematician (core contributions to mathematical logic).
3. Classify Turchin as mainly in cybernetics and philosophy.
4. Eliminate Turchin as the primary mathematician.
5. Conclude: **Anatoly Maltsev**.

Disambiguation Note
Nationality (Russia) does not help differentiate them.

Figure 9: 1-shot example used in `ParamAgent` for semantic decomposition dataset construction in multi-hop QA.

You are an AI Python assistant. You will be given some potential pitfalls and several flawed implementations for the coding challenge, as well as your previous implementation of a function, a series of unit-test results, and your self-reflection on your previous implementation. Try to avoid the errors from your previous implementation and the listed pitfalls.

Instruction: ALWAYS WRITE your full implementation (restate the function signature).

Figure 10: Instruction prompt used by `ParamAgent` to generate next-round solutions for programming tasks.

You are revising your previous answer to a mathematics problem.
You will receive:
(1) the original question,
(2) potential mistakes and pitfalls,
(3) your last answer, (4) feedback (Right or Wrong) explaining why that answer was unsatisfactory, and (5) your brief self-reflection on the mistake.

Respond with:
1. **Reasoning**: updated step-by-step thoughts.

2. **Answer**: the corrected final result.

Formatting: The final answer should be simplified to its simplest form, e.g., 25, 25_{16}, $\frac{1}{36}$, etc.

Figure 11: Instruction prompt used by `ParamAgent` to generate next-round solutions for math reasoning.

You are revising your previous answer to a multi-hop QA question.
You will receive:
(1) the original question,
(2) some key points, the underlying intent, and possible inference patterns that facilitate answering this question,
(3) your last answer,
(4) supporting context,
(5) feedback (Right or Wrong) explaining why that answer was unsatisfactory,
(6) your brief self-reflection on the mistake.

Instruction: Based on the inputs, produce a new single-phrase answer that resolves the error and fully answers the question. Output only the answer — no commentary, no code.

Figure 12: The prompt of `ParamAgent` to generate next-round answers for multi-hop QA tasks.