ReflCtrl: Controlling LLM Reflection via Representation Engineering

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Abstract

Large language models (LLMs) with Chain-of-Thought (CoT) reasoning have achieved strong performance across diverse tasks, including mathematics, coding, and general reasoning. A distinctive ability of these reasoning models is **self-reflection**: the ability to review and revise previous reasoning steps. While self-reflection enhances the reasoning performance, it also increases inference cost. In this work, we study self-reflection through the lens of **representation engineering**. We segment model's reasoning into steps, identify the steps corresponding to reflection, and extract a reflection direction in the latent space that governs this behavior. Using this direction, we propose a stepwise steering method that can control reflection frequency. We call our framework ReflCtrl. Our experiments show that: (1) for many cases the reflections are redundant, especially in stronger models (in our experiment, we can save up to 33.6% of reasoning tokens while preserving the performance), and (2) model's reflection behavior is highly correlated with internal uncertainty signal, implying self-reflection may be controlled by model's uncertainty.

1 Introduction

Large language models (LLMs) have shown great success in many reasoning-related tasks, including math, coding, and general reasoning. A common technique for enhancing LLM reasoning is Chain-of-Thought (CoT) prompting [Wei et al., 2022], which asks the model to decompose the reasoning process into intermediate steps. Recently, a new class of models has been trained to develop **native reasoning ability**, such as OpenAI's o1 [OpenAI, 2024] and DeepSeek-r1 [DeepSeekAI et al., 2025]. They can automatically generate reasoning steps before providing a response, even without being prompted to do so.

Notably, these reasoning models develop the ability to **self-reflect**, i.e. rethink their previous reasoning during training. This is described by DeepSeek-R1 [DeepSeekAI et al., 2025] as the "aha moment". The self-reflection ability is a key difference between reasoning models and their non-reasoning counterparts, and is widely believed to contribute to improved reasoning ability. Additionally, it is also a costly component in inference: our empirical study finds self-reflection consumes 25-30% of total reasoning tokens.

Despite its potential importance, the underlying mechanism of self-reflection is not yet well understood. In this work, we take the first step to investigate this phenomenon through the lens of representation engineering [Zou et al., 2023], focusing on two central research questions:

RQ1: When does the model initiate reflection during its reasoning process?

RQ2: How does reflection influence the model's reasoning performance?

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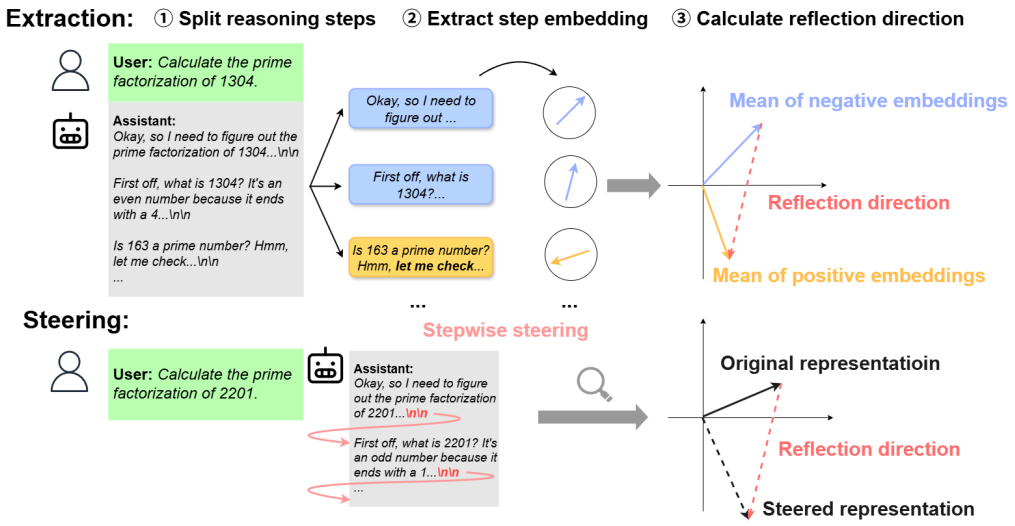


Figure 1: **Overview of the proposed ReflCtrl framework.** The model's reasoning is first segmented into steps, then reflection-related steps are identified through keywords. Finally, a reflection direction is extracted by calculating the mean difference in the latent space. This direction can be used to steer the model's self-reflection behavior via the proposed stepwise steering method, enabling control over reflection frequency and inference cost.

To answer these questions, we propose a novel method to identify the **reflection direction** in the model's latent representation space. Our steering experiments demonstrate that this direction can effectively control the number of reflections during reasoning. Our empirical analysis further reveals that in many cases, the model's reflections are redundant, offering an opportunity to reduce computational cost without sacrificing accuracy. Our contributions can be summarized as follows:

1. We identify a reflection direction in the model's representation space that controls self-reflection, enabling us to steer model's reflection behavior according to user's intention.
2. We answer **RQ1** by connecting the model's reflection direction to model's internal uncertainty. In Sec. 3.5, we show that model's activation along reflection direction can effectively predict answer's correctness. This implies model's reflection behavior may be controlled by internal uncertainty measurement.
3. Utilizing the reflection directions that we discovered, we steer model's reflection to answer **RQ2**: Empirical results suggest in many cases model's self-reflection could be redundant. Further, we design a novel stepwise steering method to address reflection redundancy. This new method reduces inference cost by up to 33.6%, while preserving reasoning performance.

2 Related works

Reasoning LLMs Motivated by the success of Chain-of-Thought reasoning, several models have been trained to enhance native reasoning capability by generating thinking steps. OpenAI's o1 [OpenAI, 2024] leverages reinforcement learning to deliberate its thinking during inference. DeepSeekAI et al. [2025] introduces a more cost-efficient training method with the Grouped Relative Policy Optimization (GRPO) algorithm, as well as its distilled variants (DeepSeek-r1-distilled) that equip smaller models with thinking ability. QwQ-32b [Team, 2024] is a medium-sized reasoning model that achieves competitive performance with DeepSeek-r1 and o1. In this work, we focus on QwQ-32B [Team, 2024] and DeepSeek-r1-distill series, as they are open-sourced, allowing us to apply representation engineering techniques.

Representation engineering on LLMs While modern LLMs demonstrate remarkable capabilities, their internal mechanism is still not fully understood. Various efforts aim to make models more steerable [Srivastava et al., 2024, Sun et al., 2024, Kulkarni et al., 2025]: among these, representation

engineering [Zou et al., 2023, Bartoszcze et al., 2025] offers a principled way to analyze and guide model behavior by directly manipulating their internal representations. Zou et al. [2023] shows that representation engineering can be applied to multiple safety-related aspects by reading and editing model's internal representation. With the rise of reasoning models, representation engineering methods specialized for these models have emerged: ThinkEdit [Sun et al., 2025b] identifies a set of neurons controlling "short-thinking" and mitigates it via weight editing. Wang et al. [2025b] identifies special experts that coordinate reasoning and improves models' reasoning performance with a training-free method called RICE. Li et al. [2025] achieves machine unlearning via activation steering. Sun et al. [2025a] design LLMs to natively support interpretable concept steering. In contrast, our work focuses on the **reflection behavior** of reasoning LLMs, which is an interesting reasoning pattern introduced in reinforcement learning but not yet systematically investigated from a representation engineering perspective.

Self-reflection. DeepSeekAI et al. [2025] report that models learn to self-reflect autonomously, described as the "aha moment". Yang et al. [2025] examine this phenomenon by comparing reasoning models with their non-reasoning counterparts in terms of linguistic patterns and description of uncertainty. Wang et al. [2025a] propose reducing excessive reflection by suppressing corresponding tokens to reduce models' overthinking. In this work, we adopt a representation engineering perspective, revealing that models' reflection is correlated with its internal uncertainty representation and can be directly controlled via our proposed method.

3 ReflCtrl: Probing and steering self-reflection

In this section, we investigate reflection behavior in reasoning models through the lens of representation engineering. We start by identifying reflection steps in the model's reasoning, then extract a reflection direction in the latent space, and finally use this direction to steer the model's behavior.

3.1 Background

Reasoning LLMs are built upon the Transformer decoder architecture [Vaswani et al., 2017], which stacks multiple identical layers. Each decoder layer l processes the hidden representation $z_l \in \mathbb{R}^d$. It consists of two major components: a self-attention block and a feed-forward MLP block. Formally, it can be written as:

$$\begin{aligned} \tilde{z}_l &= z_l + z_l^{\text{attn}},\ z_l^{\text{attn}} = \text{Attn}(\text{LN}(z_l)), \\ z_{l+1} &= \tilde{z}_l + z_l^{\text{mlp}},\ z_l^{\text{mlp}} = \text{MLP}(\text{LN}(z_l)). \end{aligned} \tag{1}$$

Here, $\text{LN}(\cdot)$ denotes layer normalization, $\text{Attn}(\cdot)$ is the self-attention block and $\text{MLP}(\cdot)$ is the feed-forward network. We denote $\tilde{z}_l$ as the intermediate state after the attention block.

3.2 Identify reflection behavior

Reasoning LLMs usually produce a long, multi-step thinking process. To facilitate our analysis of model's reasoning, we first split the generated reasoning into thinking steps. We observe that such steps are naturally separated by the token sequence "\n\n" (an empty line) in most reasoning models, with each segment representing a coherent chunk of reasoning. Therefore, we treat each segment separated by "\n\n" as the smallest unit of analysis.

To identify reflection steps, we search for specific keywords within each step that mark the start of a new reflection, e.g., "Let me think", "Wait". While a reflection may span multiple steps, we identify it by detecting its initial step containing these keywords.

3.3 Extract reflection direction

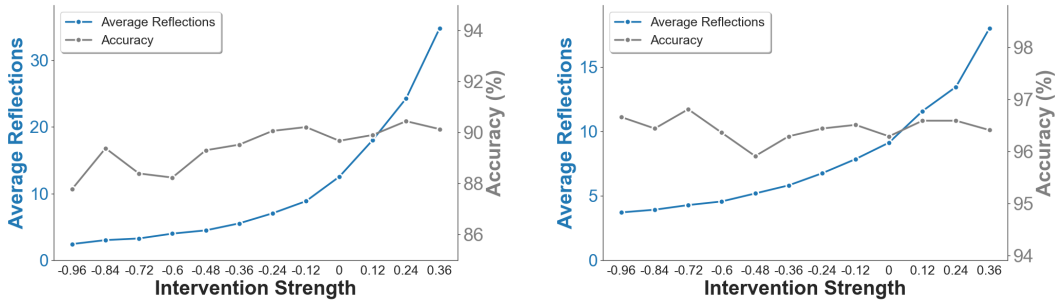
With labeled reflection steps, we next compute the reflection direction in the latent space. For each step s at layer l, we extract all internal representations from the MLP and attention output of the first token, denoted as $z_l^{\{\text{attn,mlp}\}}(s)$. We use the first token because it captures the model's internal state when reflection is initialized, allowing us to investigate the triggering mechanism of reflections. The reflection direction is then defined as the mean difference between reflection and non-reflection

embeddings:

$$d_l^{\{\text{attn,mlp}\}} = \frac{1}{|\text{R}|} \sum_{s \in \text{R}} z_l^{\{\text{attn,mlp}\}}(s) - \frac{1}{|\text{NR}|} \sum_{s \in \text{NR}} z_l^{\{\text{attn,mlp}\}}(s), \tag{2}$$

where R and NR are the sets of reflection and non-reflection steps, respectively.

3.4 Steer model's reasoning



(a) DeepSeek-R1 Llama 8b

(b) QwQ-32B

Figure 2: **Accuracy and number of reflection steps under different intervention strengths.** Results are shown for DeepSeek-R1 Llama 8b (distilled model) and QwQ-32B (non-distilled model) on GSM8k. Accuracy remains largely stable, while the number of reflection steps decreases as intervention strength decreases.

With the reflection direction, we can steer the model's reasoning by injecting this direction into its internal representations. Specifically, the intervention is applied by directly adding the direction vector:

$$z_{l,\text{intv}}^{\{\text{attn,mlp}\}} = z_l^{\{\text{attn,mlp}\}} + \lambda d_l^{\{\text{attn,mlp}\}}. \tag{3}$$

Here, z_l denotes the model output at layer l, and λ is a hyperparameter controlling the intervention strength.

In standard representation-steering approaches, the intervention is applied at **every token generation step**. However, at high intervention strengths, this may push the model's representation far from the training distribution and degrade model's performance.

To address this, we propose **stepwise steering**: instead of applying intervention on every token, we apply it only when the model **begins a new thinking step**. Specifically, the intervention is triggered when the last generated token matches the step delimiter "\n\n". As shown in figs. 4a and 4b, this method preserves intervention effects while avoiding the performance drop observed in full-token steering at high intervention strengths, allowing users to have more control on inference tokens without sacrificing performance.

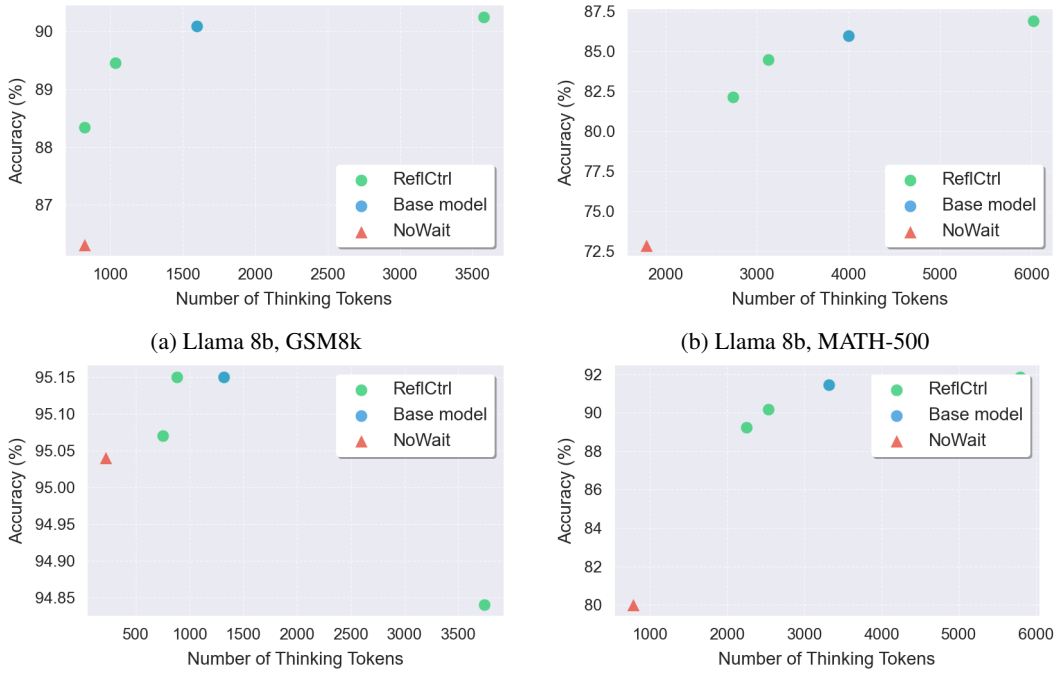
3.5 Probing model's uncertainty on reflection direction

Another application of reflection direction is to investigate **RQ1** we proposed in Sec. 1: *When will self-reflection be triggered?* Our hypothesis is that: *Reasoning LLMs trigger reflection when their internal uncertainty is high.*

To verify our hypothesis, we need an approach to quantify the model's uncertainty during the generation process. Here, we follow [Mielke et al., 2022] and train an auxiliary classifier to predict model answer correctness. For each instance, we compute the projection of the intermediate representation on the reflection direction across all layers. These values are concatenated into a feature vector p_{intv}:

$$p_{\text{intv}} = \text{concat}(\{p_l^{\text{attn}}\}_{l=1}^{N_{\text{layer}}}, \{p_l^{\text{mlp}}\}_{l=1}^{N_{\text{layer}}}), \tag{4}$$

where $p_l^{\{\text{attn,mlp}\}} = cos(d_l^{\{\text{attn,mlp}\}}, z_l^{\{\text{attn,mlp}\}})$. We extract the feature vector p_{intv} from the end of thinking token (</think> for models we use in the paper), and train a logistic regression model



(a) Llama 8b, GSM8k

(b) Llama 8b, MATH-500

(c) Qwen 14b, GSM8k

(d) Qwen 14b, Math-500

Figure 3: **Accuracy versus reasoning token usage for ReflCtrl compared with NoWait [Wang et al., 2025a].** Results are shown for DeepSeek-R1 Llama 8b and DeepSeek-R1 Qwen 14b across GSM8k and MATH-500 benchmarks. ReflCtrl allows fine-grained control over the trade-off between accuracy and reasoning cost via intervention strength, while NoWait can only suppress reflections entirely. Additionally, ReflCtrl achieves lower performance loss for similar token usage.

upon it on GSM8k training dataset to predict whether model's answer is correct. If our hypothesis is correct, the classifier should achieve high accuracy, since the reflection direction is aligned with the model's uncertainty. As the baseline, we use the representation of the last token at the final layer. Results on the GSM8k test set (table 1) show that features derived from the reflection direction achieves higher AUROC and F1 scores, despite having fewer dimensions. This suggests that **model's uncertainty information is encoded in the reflection direction**, and may be a key factor in triggering self-reflection.

Model	final layer embedding		reflection direction	
	AUROC	F1	AUROC	F1
deepseek-llama-8b	0.736	0.946	**0.772**	**0.948**
qwq-32b	0.555	0.636	**0.564**	**0.839**
deepseek-qwen-14b	0.716	0.929	**0.850**	**0.976**

Table 1: **Probing results for uncertainty detection.** We train a logistic regression classifier to predict answer correctness using (i) the last token embedding at the final layer or (ii) feature vector p_{intv} derived from reflection direction. Reflection-based features achieve higher AUROC and F1 scores despite lower dimensionality, suggesting that uncertainty is encoded in the reflection direction.

4 Experiments

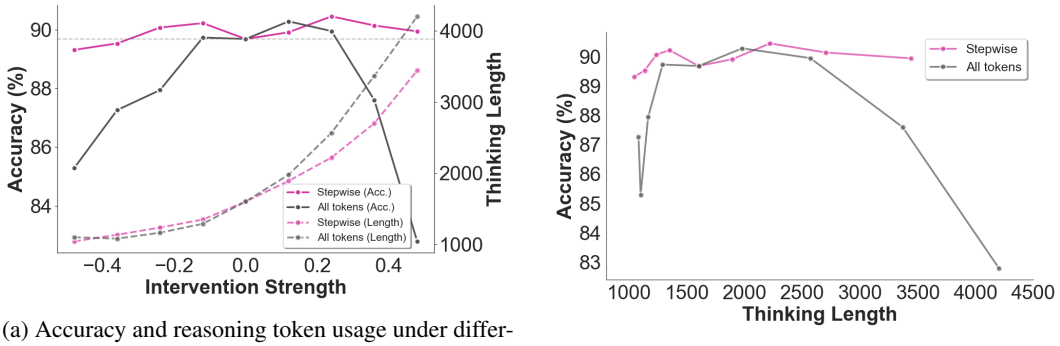
In this section, we conduct an empirical study of our ReflCtrl framework, evaluating how reflection influence model's performance (**RQ2**) and how our stepwise steering reduces reasoning budget.

4.1 Settings

Models. In this work, we primarily study the DeepSeek-R1-Distilled series of models, including the distilled version of Qwen-2.5 14B and Llama 8B, as these models are publicly available. We also evaluate the QwQ-32B model as a non-distilled reasoning model.

Datasets. For math tasks, we use the GSM8k and MATH-500 as test datasets. For general reasoning tasks, we use the MMLU benchmark, selecting three subsets: Profeessional accounting, highschool computer science and formal logic.

Generation settings. We follow the standard generation configurations for each model. For math tasks, we use the prompt "Please reason step by step, and put your final answer within \boxed" after each question. For MMLU benchmark, we use the prompt ""Please reason step by step, and put your final answer (only the letter) within \boxed." The maximum completion tokens are set to 8192, except for MATH-500 where we use 16384 due to its higher complexity.



(a) Accuracy and reasoning token usage under different intervention strength.

(b) Accuracy under different reasoning token usage.

Figure 4: **Comparison of stepwise versus all-token steering.** (a) Accuracy under different intervention strengths when interventions are applied at the start of each reasoning step (stepwise) or at every token (all-token). (b) Accuracy versus reasoning token usage under the two approaches. Stepwise steering preserves accuracy while reducing cost, whereas all-token steering causes significant degradation at large intervention strengths.

Reflection direction extraction. To extract the reflection direction, we use the GSM8k dataset to generate model responses. Then, we apply the method we propose in Sec. 3 to extract the direction. The final step in the reasoning process is omitted as we observe that it is usually a conclusion sentence unrelated to reasoning.

Steering. For the results we show in this section, we apply the stepwise steering method we propose in Sec. 3 unless otherwise specified. The intervention is applied in all layers except the first and last six layers. We further discuss this choice in Sec. 4.4.

4.2 Main experiments

In this section, we study **RQ2:** *How does reflection influence the model's reasoning performance*. We begin with DeepSeek-R1 Llama 8b model and test it on GSM8k and MATH-500 datasets with $N = 10$ samples per question. We measure the correctness rate and the reflection rate (number of reflection steps / number of total reasoning steps). As shown in Fig. 5, the correctness rate drops as reflection rate goes higher. However, this does not indicate self-reflection hurts model performance: one possible reason is that the model tends to reflect more when the question is difficult, and the accuracy is generally lower for harder question. We further verify this hypothesis in Sec. C.

To understand the causal relationship between reflection and model performance, we apply different strengths of interventions to the model to intervene self-reflection, and check the model's performance change under intervention. Fig. 2 shows the accuracy and number of reflection steps under different intervention strengths. We choose DeepSeek-R1 Llama 8b as the distilled model and QwQ-32b for

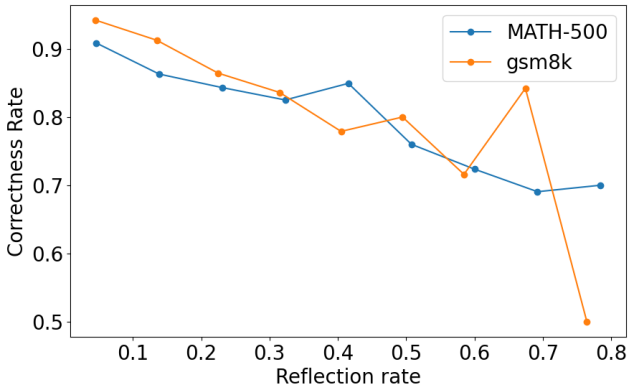


Figure 5: Relationship between correctness rate and reflection rate on MATH-500 and GSM8k datasets. Higher reflection frequency correlates with lower accuracy, partly due to more reflections are generated on difficult questions.

Category	Model	Metric	Reflection Strength			
			-0.96	-0.48	0	0.48
GSM-8k	DS-Llama-8b	Accuracy	88.34%	89.46%	90.09%	90.25%
		Tokens	821.0	1032.6	1595.7	3577.1
	QwQ-32b	Accuracy	96.36%	96.50%	96.50%	96.44%
		Tokens	1006.7	1162.5	1488.6	2256.9
	DS-qwen-14b	Accuracy	95.07%	95.15%	95.15%	94.84%
		Tokens	747.8	880.2	1315.9	3746.4
MATH-500	DS-Llama-8b	Accuracy	82.14%	84.46%	85.98%	86.90%
		Tokens	2738.1	3123.8	4000.7	6017.8
	QwQ-32b	Accuracy	92.72%	92.58%	93.06%	93.08%
		Tokens	2992.9	3253.4	3786.0	5028.9
	DS-qwen-14b	Accuracy	89.22%	90.18%	91.44%	91.86%
		Tokens	2247.1	2534.7	3315.3	5789.0

Table 2: **Accuracy and average reasoning token usage under different intervention strengths.** Results are reported on GSM8k and MATH-500 datasets for DeepSeek-R1 Llama 8B, and DeepSeek-R1 Qwen 14B, and QwQ-32B. The numbers reported are averaged over 10 runs. Negative intervention strengths reduce reflection frequency and reasoning token usage with minimal accuracy loss, suggesting potential reflection redundancy.

non-distilled model. The results show that in both cases, interventions effectively control the number of reflection steps. In terms of accuracy, DeepSeek-R1 Llama 8b gains marginal improvement with more reflections, while QwQ-32b is largely insensitive to the number of reflections. We observe:

1. Most models are less sensitive to additional reflections. From the table, the only model that benefits from positive intervention (more reflections) is the DeepSeek-Llama-8b distilled model, which receives 0.16% and 0.92% accuracy gain on GSM8k and MATH-500, respectively, at the cost of around 2000 additional reasoning tokens for each question.
2. Reflection redundancy exists in many cases, especially for stronger models. For example, in QwQ-32b model, the largest model in our test, the performance loss is only 0.14% and 0.34% on two datasets at intervention strength -0.96, while the reasoning token budget is reduced by 32.4% and 21.0%, respectively. This demonstrates that reasoning cost, which is substantially higher than non-reasoning models, can be reduced with minimal accuracy loss.

To further understand how reflection affects the trade-off between thinking cost and performance, we calculate the reasoning token usage and accuracy under different intervention strengths and report the results in table 2. For each question, we sample 10 responses and report the mean result. The results confirm our findings, showing that in many cases, reflections can be reduced without sacrificing performance.

Category	Model	Metric	Reflection Strength			
			-0.96	-0.48	0	0.48
Professional accounting	DS-Llama-8b	Accuracy	50.1%	53.4%	56.5%	57.3%
		Tokens	1453.6	1668.8	2097.5	2807.7
	DS-qwen-14b	Accuracy	78.5%	76.8%	77.8%	77.6%
		Tokens	983.9	1103.1	1482.1	2470.1
	QwQ-32b	Accuracy	89.3%	89.5%	88.5%	89.2%
		Tokens	1231.2	1313.7	1648.0	2234.3
Highschool computer science	DS-Llama-8b	Accuracy	79.6%	82.7%	87.3%	88.0%
		Tokens	1016.1	1157.9	1365.4	1970.4
	DS-qwen-14b	Accuracy	95.2%	95.4%	95.0%	94.8%
		Tokens	711.9	787.9	933.5	1498.7
	QwQ-32b	Accuracy	96.6%	96.2%	96.7%	97.0%
		Tokens	771.6	741.9	871.0	1004.7
Formal logic	DS-Llama-8b	Accuracy	60.5%	61.0%	62.1%	62.7%
		Tokens	2266.5	2586.9	3378.3	4553.5
	DS-qwen-14b	Accuracy	91.8%	92.2%	92.6%	92.8%
		Tokens	1287.2	1440.1	1891.4	3196.5
	QwQ-32b	Accuracy	96.3%	95.5%	95.7%	96.0%
		Tokens	1481.4	1447.8	1716.6	2175.6

Table 3: **Accuracy and reasoning token usage under different intervention strengths(λ) on MMLU subsets.** The numbers reported are averaged over 10 runs. Smaller models (e.g., DS-Llama-8B) are more sensitive to reflection reduction, while larger models (DS-Qwen-14B and QwQ-32B) maintain accuracy with fewer reflections, saving up to 33.6% of reasoning tokens.

To evaluate the effectiveness of ReflCtrl, we compare it with the baseline, NoWait [Wang et al., 2025a]. NoWait is a recent work that reduces redundant reflection by directly suppressing corresponding reflection tokens. We plot the accuracy versus number of thinking tokens in Fig. 3. From the results, we can see that ReflCtrl is more flexible: the intervention strength can control the trade-off between performance and cost, while NoWait can only completely disable reflection. Additionally, ReflCtrl generally incurs smaller performance loss under similar token budget.

4.3 Stepwise steering

In this section, we study the stepwise steering strategy for controlling model reflection. We compare it with a baseline method where the intervention is applied to all generation tokens. In this experiment, we use DeepSeek-R1 Llama 8b as the base model and evaluate on GSM8k dataset. As shown in figs. 4a and 4b, we observe that:

1. Under the same intervention strength, stepwise intervention achieves performance similar to intervention at all tokens. The baseline method produces stronger effects when applying positive intervention, i.e. increasing model's reflection.

2. In terms of accuracy, stepwise intervention maintains accuracy close to the original model, whereas the baseline method degrades performance significantly at larger intervention strengths (< -0.2 or > 0.3). Fig. 4b further shows that, under the same thinking token usage, stepwise intervention generally achieves higher accuracy.

4.4 Ablation study: impact of layers

In this section, we study the effect of applying intervention at different layers of the LLM. We experiment with two strategies: Skipping the first k layers and skipping the last k layers. The results in Fig. 6 indicate that the performance is best when skipping both the first and last six layers. We adopt this configuration accordingly in our main experiments.

4.5 Non-mathematical benchmarks

To evaluate the proposed ReflCtrl on non-mathematical reasoning tasks, we conduct extensive experiments on MMLU subsets. As shown in table 3, we observe a similar phenomenon as in math tasks. In general, the smallest model, DeepSeek Llama 8b, is most sensitive to reflection. In contrast, the larger DeepSeek Qwen 14b and QwQ-32b are hardly affected by the reduction of reflections. Using the proposed stepwise steering, up to 33.6% of reasoning tokens can be saved.

5 Conclusion and limitation

In this work, we propose ReflCtrl, a representation engineering framework for understanding and steering self-reflection behavior in reasoning LLMs. By segmenting the model's reasoning into thinking steps and identifying reflection-related steps, we extract a reflection direction in the latent space, enabling direct control over self-reflection frequency during inference. We further introduce a **stepwise steering** strategy that only applies interventions at the start of new thinking steps, substantially reducing reasoning token usage while preserving performance. Across multiple math and general-domain reasoning benchmarks, we find that:

1. Reflection redundancy is common, particularly in stronger models where minimal accuracy loss is observed when reflections are reduced.
2. Reflection direction is correlated with internal uncertainty signals, implying that the reflection behavior may be controlled by model's internal uncertainty perception.
3. Stepwise steering can largely mitigate performance loss. Compared with token-level intervention, stepwise steering can achieve similar intervention performance with over 5% accuracy improvement.

6 Limitations

Despite these promising results, our work also has some limitations. First, the identification of reasoning steps relies on keyword search, which may be model specific since different models could prefer different reflection cues. Second, our ReflCtrl only works for open-source models and it remains unclear whether it generalizes to SOTA closed-source models such as GPT-4 or Claude, which is a shared limitation of representation engineering methods.

For future work, we believe that developing uncertainty-aware dynamic steering is a promising direction: our results preliminarily show a connection between uncertainty and self-reflection. The current steering method applies a fixed strength across all questions and throughout the generation process. Enabling the model to dynamically adjust steering strength during inference could substantially improve reflection efficiency and further reduce inference cost in reasoning LLMs.

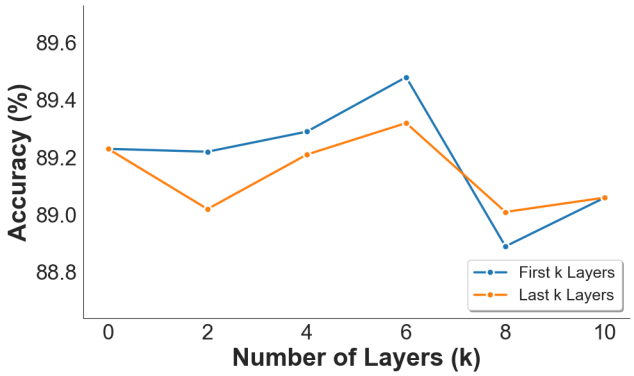


Figure 6: **Effect of applying interventions to different layers of the LLM.** We vary the number of skipped layers at the bottom and top of the network, with intervention strength fixed at $\lambda = -0.48$. Accuracy is highest when skipping the first and last six layers, which we adopt as the default configuration in our main experiments.

References

Lukasz Bartoszcze, Sarthak Munshi, Bryan Sukidi, Jennifer Yen, Zejia Yang, David Williams-King, Linh Le, Kosi Asuzu, and Carsten Maple. Representation engineering for large-language models: Survey and research challenges. *arXiv preprint arXiv:2502.17601*, 2025.

DeepSeekAI, Daming Guo, Dayi Yang, Zehui Ren, Zhangli Sha, Zhe Fu, Zhean Xu, Zhenda Xie, Zhengyan Zhang, Zhewen Hao, Zhicheng Ma, Zhigang Yan, Zhiyu Wu, Zihui Gu, Zijia Zhu, Zijun Liu, Zilin Li, Ziwei Xie, Ziyang Song, Zizheng Pan, Zhen Huang, Zhipeng Xu, Zhongyu Zhang, and Zhen Zhang. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning, 2025.

Akshay Kulkarni, Ge Yan, Chung-En Sun, Tuomas Oikarinen, and Tsui-Wei Weng. Interpretable generative models through post-hoc concept bottlenecks. In *CVPR*, 2025.

Yongce Li, Chung-En Sun, and Tsui-Wei Weng. Effective skill unlearning through intervention and abstention. *NAACL*, 2025.

Sabrina J. Mielke, Arthur Szlam, Emily Dinan, and Y-Lan Boureau. Reducing conversational agents' overconfidence through linguistic calibration. *Transactions of the Association for Computational Linguistics*, 10:857–872, 2022. doi: 10.1162/tacl_a_00494. URL https://aclanthology.org/2022.tacl-1.50/.

OpenAI. Openai o1 system card, 2024.

Divyansh Srivastava, Ge Yan, and Tsui-Wei Weng. Vlg-cbm: Training concept bottleneck models with vision-language guidance. *NeurIPS*, 2024.

Chung-En Sun, Tuomas Oikarinen, and Tsui-Wei Weng. Crafting large language models for enhanced interpretability. *NeurIPS MI Workshop*, 2024.

Chung-En Sun, Tuomas Oikarinen, Berk Ustun, and Tsui-Wei Weng. Concept bottleneck large language models. In *ICLR*, 2025a.

Chung-En Sun, Ge Yan, and Tsui-Wei Weng. Thinkedit: Interpretable weight editing to mitigate overly short thinking in reasoning models. *EMNLP*, 2025b.

Qwen Team. Qwq: Reflect deeply on the boundaries of the unknown, November 2024. URL https://qwenlm.github.io/blog/qwq-32b-preview/.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

Chenlong Wang, Yuanning Feng, Dongping Chen, Zhaoyang Chu, Ranjay Krishna, and Tianyi Zhou. Wait, we don't need to" wait"! removing thinking tokens improves reasoning efficiency. *arXiv preprint arXiv:2506.08343*, 2025a.

Mengru Wang, Xingyu Chen, Yue Wang, Zhiwei He, Jiahao Xu, Tian Liang, Qiuzhi Liu, Yunzhi Yao, Wenxuan Wang, Ruotian Ma, et al. Two experts are all you need for steering thinking: Reinforcing cognitive effort in moe reasoning models without additional training. *arXiv preprint arXiv:2505.14681*, 2025b.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In *Advances in Neural Information Processing Systems*, volume 35, pages 24824–24837. Curran Associates, Inc., 2022.

Shu Yang, Junchao Wu, Xin Chen, Yunze Xiao, Xinyi Yang, Derek F Wong, and Di Wang. Understanding aha moments: from external observations to internal mechanisms. *arXiv preprint arXiv:2504.02956*, 2025.

Andy Zou, Long Phan, Sarah Chen, James Campbell, Phillip Guo, Richard Ren, Alexander Pan, Xuwang Yin, Mantas Mazeika, Ann-Kathrin Dombrowski, et al. Representation engineering: A top-down approach to ai transparency. *arXiv preprint arXiv:2310.01405*, 2023.

Table of Contents

A Reasoning sample of LLM

Fig. 7 shows an example of LLM reasoning process. From the figure, we can see:

1. The model's reasoning is organized as separated steps separated by "\n\n".
2. The reflection process of model, marked as red in the figure, is triggered by specific keywords like "wait" in this example.

This justifies our reflection direction extraction and intervention method.

Question:

Janet's ducks lay 16 eggs per day. She eats three for breakfast every morning and bakes muffins for her friends every day with four. She sells the remainder at the farmers' market daily for $2 per fresh duck egg. How much in dollars does she make every day at the farmers' market?

Thinking Process:

Okay, let me try to figure out how much Janet makes every day at the farmers' market. So, the problem says that Janet's ducks lay 16 eggs per day. She eats three for breakfast every morning and bakes muffins for her friends every day with four. She sells the remainder at the farmers' market daily for $2 per fresh duck egg. I need to find out how much she makes each day. Hmm, let me break this down step by step.

First, let me figure out how many eggs Janet starts with each day. The problem says she lays 16 eggs per day. So, she begins with 16 eggs. Then she eats three for breakfast every morning. So, she uses 3 eggs for breakfast. After that, she bakes muffins for her friends, using four eggs each day. So, she uses 4 eggs for baking.

Wait, so she uses 3 eggs in the morning and 4 eggs for the muffins. Let me calculate the total number of eggs she uses in a day. So, 3 plus 4 is 7 eggs. So, she uses 7 eggs each day.

She starts with 16 eggs, uses 7, so how many eggs does she have left? Let me subtract 7 from 16. 16 minus 7 is 9. So, she has 9 eggs left after using them for breakfast and baking.

Now, these remaining 9 eggs, she sells at the farmers' market. The problem says she sells each fresh duck egg for $2. So, I need to figure out how much money she makes from selling these 9 eggs.

To find the total revenue, I can multiply the number of eggs she sells by the price per egg. So, 9 eggs times $2 per egg. Let me compute that. 9 times 2 is 18. So, she makes $18 each day at the farmers' market.

Wait, let me double-check my steps to make sure I didn't make a mistake. She lays 16 eggs, uses 3 for breakfast, 4 for muffins, which totals 7 eggs used. 16 minus 7 is 9 eggs left. 9 eggs times $2 is $18. Hmm, that seems right.

I think that makes sense. So, she starts with 16, uses 7, sells 9, making her $18 each day. Yeah, that adds up.

Just to visualize it, maybe I can represent it with some equations. Let me define variables for clarity. Let E be the number of eggs laid per day, which is 16. Let B be the number of eggs she eats for breakfast, which is 3. Let M be the number of eggs she uses for muffins, which is 4. So, the total eggs used per day would be B plus M, so 3 plus 4 is 7.

Then, the eggs she has left would be E minus \(B + M\), which is 16 minus 7, which is 9. Then, the revenue R from selling these remaining eggs is 9 times the price per egg, which is 2. So, R is 9 times 2, which is 18.

Yes, that all checks out. So, I think I did it correctly. She makes $18 each day at the farmers' market.

Final Answer Janet makes \boxed{18} dollars every day at the farmers' market.

Figure 7: Sample reasoning process of DeepSeek-r1-llama-8b model on a gsm8k question.

B Reflection direction attribution to attention heads

In this section, we study the attribution of reflection direction to individual attention heads. We first take the reflection direction at self-attention layers from a DeepSeek-r1-qwen-1.5b model. Then, we compare it with the average activation of individual attention heads. We calculate the projection of average activation on the reflection direction and plot the heatmap in Fig. 8. From the figure, we can see:

1. Last layer (layer 27) has largest projection magnitude among all the layers. The reason may be this layer controls generation of keywords directly controlling reflection (e.g., “wait").
2. The heads that have positive projection on reflection direction are sparse and located mostly in deeper layers of the model. These heads may direction control model's reflection behavior.

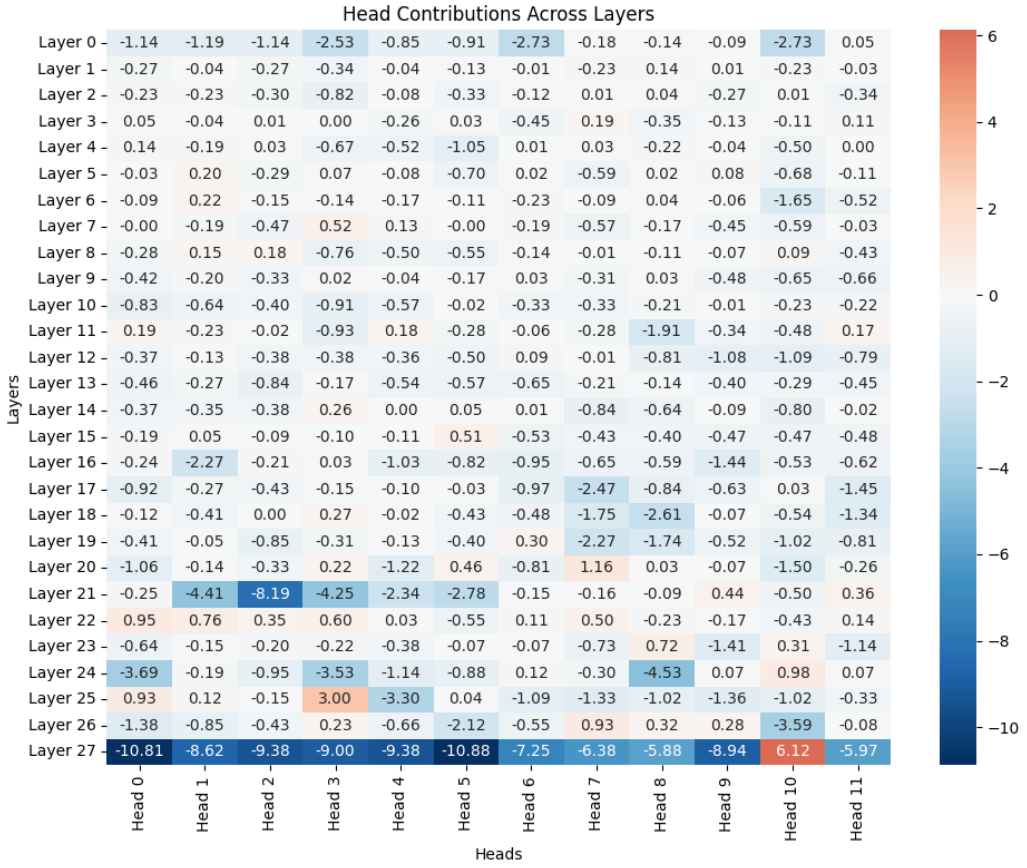


Figure 8: Projection of average activation of attention heads on the reflection direction. We use GSM8k dataset and extract results on a DeepSeek-R1 qwen 1.5b model which has 28 layers and 12 attention heads per layer.

C Study of model performance on reflection rate

In this section, we further study how the model's performance depends on the reflection rate by categorizing the questions into three classes according to model's accuracy on this question: Hard($acc < 50\%$), Medium ($50\% \leq acc \leq 80\%$) and Easy ($acc > 80\%$). We study the correctness vs. reflection rate for these three categories individually and show the results in Fig. 9. We show the results for base model without intervention and with intervention of -0.98. From the results, we can see:

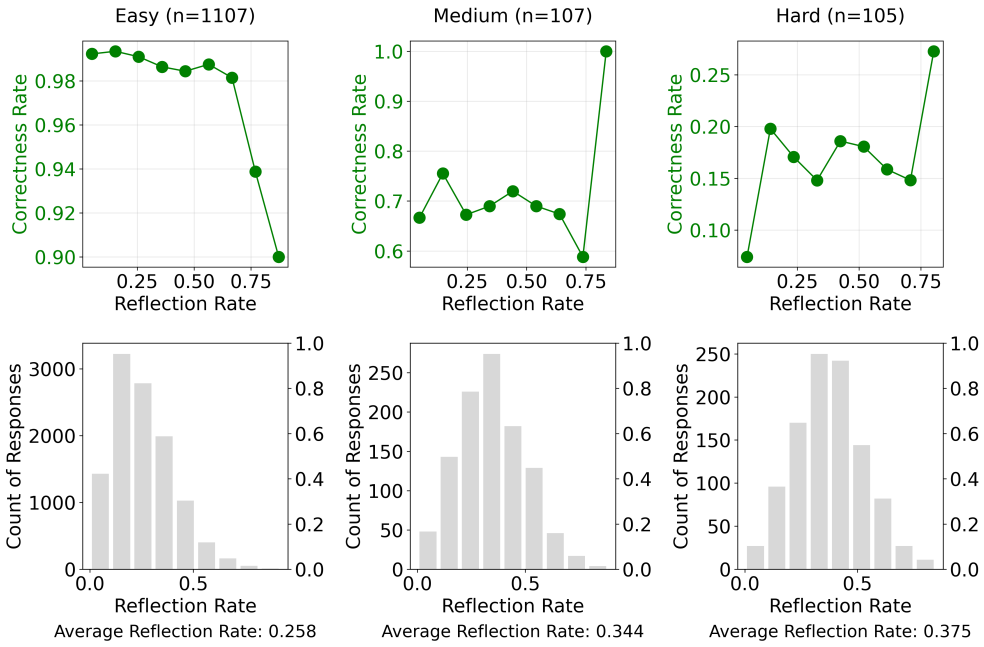
1. For harder question, model tends to reflect more: The easy questions have an average reflection rate of 25.8% and the hard questions are 37.5%.
2. Within each category, the correctness rate is not correlated with reflection rate, excluding some outliers due to rare samples. This hints reflection of models might be redundant.
3. After intervention, reflection rates of all categories are reduced, while harder questions still get more reflections.

D LLM usage

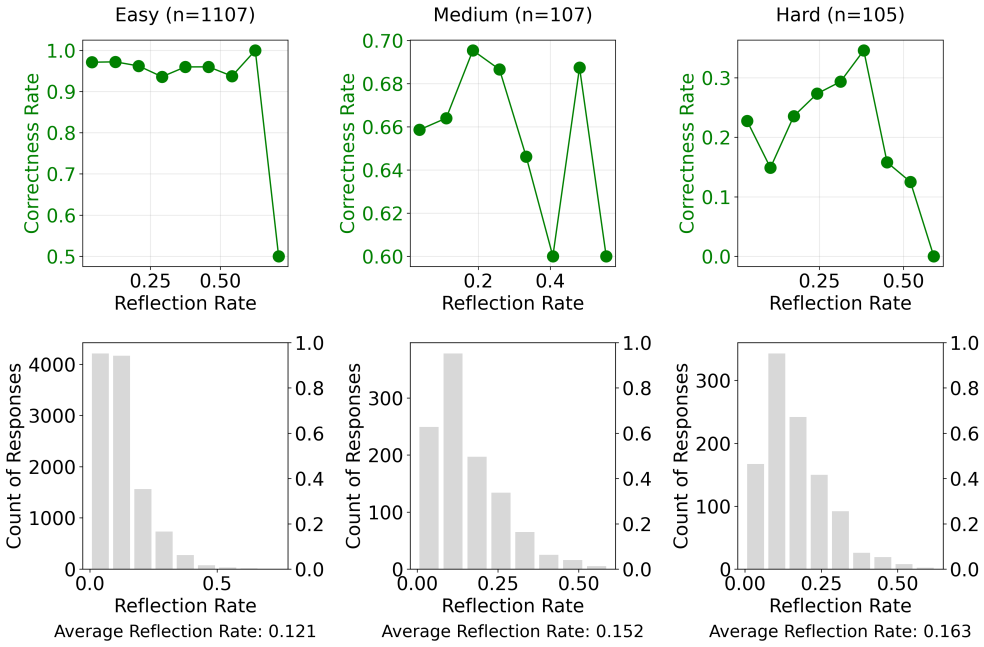
In the writing of this paper, LLMs are utilized to check grammar errors and typos as well as improving general writing.

E Computational resources

The main experiments is conducted on 8 NVIDIA 6000 ada gpus for around 200 hours.



(a) Base model. Top: Correctness rate vs. reflection rate. Bottom: Reflection rate distribution.



(b) Intervention. Top: Correctness rate vs. reflection rate. Bottom: Reflection rate distribution.

Figure 9: Correctness rate and reflection rate on three categories of questions for DeepSeek-R1 llama 8b model on GSM8k dataset.