Probing and Controlling Self-Reflection in Language Models

Abstract

Self-reflection—the ability of a large language model (LLM) to revisit, evaluate, and revise its own reasoning—has recently emerged as a powerful behavior enabled by reinforcement learning with verifiable rewards (RLVR). While self-reflection correlates with improved reasoning accuracy, its origin and underlying mechanisms remain poorly understood. In this work, *we first show that self-reflection is not exclusive to RLVR fine-tuned models: it already emerges, albeit rarely, in pretrained models.* To probe this latent ability, we introduce Reflection-Inducing Probing, a method that injects reflection-triggering reasoning traces from fine-tuned models into pretrained models. This intervention raises self-reflection frequency of Qwen2.5 from 0.6% to 38.9%, revealing a hidden capacity for reflection. Moreover, our analysis of internal representations shows that both pretrained and fine-tuned models maintain hidden states that distinctly separate self-reflective from non-reflective contexts. Leveraging this observation, *we then construct a self-reflection vector, a direction in activation space associated with self-reflective reasoning.* By manipulating this vector, we enable bidirectional control over the self-reflective behavior for both pretrained and fine-tuned models. Experiments across multiple reasoning benchmarks show that enhancing these vectors improves reasoning performance by up to 13.7, while suppressing them reduces computational cost, providing a flexible mechanism to navigate the trade-off between reasoning quality and efficiency without requiring additional training. Our findings further our understanding of self-reflection and support a growing body of work showing that understanding model internals can enable precise behavioral control.

1 Introduction

Reinforcement Learning with Verifiable Rewards (RLVR) has emerged as a powerful technique for enhancing the reasoning abilities of large language models (LLMs), enabling learning from outcome-level feedback across diverse tasks (Xu et al., 2025; WANG et al., 2025; Mroueh, 2025). In a nutshell, RLVR optimizes for end-task success, enabling models to autonomously explore and discover novel reasoning strategies at scale without relying on explicit supervised signals from human expertise (Zhao et al., 2025b; Ferrag et al., 2025; Su et al., 2025). Notably, it has been reported (Guo et al., 2025; Liu et al., 2025c; Zeng et al., 2025) that such training induces new emergent behaviors, such as self-reflection—the ability of a model to revisit, evaluate, and revise its prior outputs. For instance, the DeepSeek-R1 report (Guo et al., 2025) highlights that RLVR-trained models often generate tokens such as "wait", interpreted as signals of internal deliberation or critique.

At the same time, a growing body of work raises an important question: does RLVR truly incentivize new reasoning capabilities beyond those already present in the base pretrained model, or does it primarily elicit and amplify latent behaviors through training and decoding strategies (Yue et al., 2025)? This ongoing debate calls for a more principled understanding of what is genuinely learned versus what is revealed. In this work, we focus on one such behavior—self-reflection—as a concrete lens to study this question.

Despite these observations of self-reflection emerging under RLVR, it remains unclear whether such behaviors are genuinely induced by RLVR or arise from latent capabilities in the base model, and more fundamentally, why and how such reflective behaviors emerge. Answering this question is crucial for understanding the foundations of reasoning in LLMs and guiding future methods for enhancing their performance. Moreover, empirical studies have shown that reflection correlates with more accurate and robust reasoning (Zuo et al.,

Figure 1: The overall pipeline of our method. **Left:** We identify self-reflection behavior in LLMs by using LLM-as-a-judge to locate self-reflection tokens (e.g., *wait*), and extract the corresponding Reflection-Inducing Tokens (RIT) and Non-Reflection-Inducing Tokens (NIT) from their context (see 4.2 for definitions). **Middle:** Hidden state analysis reveals that both $\mathcal{A}_{\texttt{pt}}$ and $\mathcal{A}_{\texttt{ft}}$ exhibit clear geometric separation between reflection and non-reflection states, indicating that $\mathcal{A}_{\texttt{pt}}$ retains latent self-reflection capacity despite its low surface-level reflection rate (0.6%). Transplanting pre-reflection responses from $\mathcal{A}_{\texttt{ft}}$ into $\mathcal{A}_{\texttt{pt}}$ confirms this capacity, boosting its self-reflection rate to 38.9%. **Right:** Leveraging RIT and NIT hidden states collected from both models, we construct a self-reflection vector and apply linear steering. Positive steering strength improves task performance, while negative steering yields more concise responses, demonstrating bidirectional control over the self-reflection behavior.

2025; Yue et al., 2025; Liu et al., 2024a), and that prompting models to explicitly "wait" or reflect can further improve performance with test-time computing. However, this benefit may come at a cost: reflection can increase inference time, introduce unnecessary verbosity, and reduce computational efficiency (Yang et al., 2025b; Renze & Guven, 2024; Sui et al., 2025). These findings highlight not only the need to understand self-reflection in LLMs, but also the importance of controlling it to balance reasoning quality and efficiency. These gaps motivate this work to study the following research questions:

Is self-reflection a novel behavior induced by RLVR, or does it already emerge during pretraining? Can we control self-reflection in LLMs to balance performance and computational efficiency?

Contribution In this work, we provide affirmative answers to both questions. First, we compare the reasoning behaviors of pretrained models and fine-tuned models (either via RLVR or distillation), and verify that self-reflection is already present in the pretrained model, albeit at a much lower frequency. Next, we analyze the hidden representations associated with reflective versus non-reflective reasoning, and find that they exhibit distinct activation patterns. Furthermore, we show that the degree of self-reflection can be modulated by a single direction in the representation space. Our contribution can be summarized as follows.

- **Self-Reflection already emerges during pretraining:** We demonstrate that self-reflection capabilities naturally exist in pretrained models and are not solely artifacts of RLVR. However, the frequency of such behavior is extremely low—for example, only 0.6% as shown in Figure 1. To isolate the model's capacity for self-reflection from its general reasoning ability, we propose a method, called *reflection-inducing probing*, that inserts reasoning traces—specifically, those that trigger self-reflection in a fine-tuned reasoning model—into the input of the pretrained model, and then measures whether the latter produces reflection in response. Using reflection-inducing probing, we observe that the pretrained model exhibits reflection with a frequency of 38.9%, significantly higher than the baseline of 0.6%, though still lower than the fine-tuned model (which is almost 100%). Through comparative analysis of hidden representations, we show that pretrained models maintain internal structures that distinguish reflective behavior from

non-reflective contexts—similar to fine-tuned models—further suggesting that pretrained models already possess self-reflection capabilities.

- **The degrees of self-reflection can be modulated by a single direction:** Motivated by the separability of reflective and non-reflective contexts in the hidden representation space, we use the method of difference-in-means (Rimsky et al., 2024) to construct a *self-reflection direction*, enabling control over self-reflection behavior for both pretrained and fine-tuned models. Our experiments demonstrate that this control mechanism offers a tunable trade-off between accuracy and efficiency: enhancing reflection improves accuracy on benchmarks by up to 13.7%, while suppressing it reduces output length by up to 32% without significant performance degradation. We further show that this direction transfers robustly across diverse tasks—including mathematical and scientific reasoning—highlighting its universality as a shared, task-agnostic mechanism.

2 Related Work

2.1 Features as Directions

Extracting feature directions, often derived from contrastive pairs of inputs, is an established technique for analyzing and manipulating neural network representations (Rimsky et al., 2024; Burns et al., 2022; Zou et al., 2023). It is widely recognized that adding such feature vectors to the model's residual stream can modify its behavior, although the optimal intervention points and specific methodologies remain areas of active research (Von Rütte et al., 2024; Jorgensen et al., 2023).

Several studies suggest that directions within the activation space capture semantic features more effectively or interpretably than individual neurons (Geiger et al., 2024; Park et al., 2023; Bolukbasi et al., 2016). Recent approaches utilize techniques like sparse autoencoders to discover these feature directions in a supervised manner (Huben et al., 2024). However, alternative methods such as Difference-in-Means (Arditi et al., 2024) have demonstrated strong performance, sometimes exceeding that of sparse autoencoders, in specific applications like concept detection and model steering (Wu et al., 2025). Furthermore, the underlying assumption that features can be represented linearly has proven effective in tasks such as targeted concept erasure within language models (Shao et al., 2023; Belrose et al., 2023; Feng et al., 2025; Zhu et al., 2025).

2.2 Self-Reflection in Language Models

The concept of self-reflection in language models has gained increasing attention as a mechanism for improving reasoning quality and alignment. Recent studies (Lightman et al., 2024; Madaan et al., 2023; Puerto et al., 2024; Zelikman et al., 2022; Lightman et al., 2023; Li et al., 2025) have explored how prompting models to generate intermediate reflections, critiques, or alternative solutions can improve final outputs in tasks such as math problem solving, programming, and factual reasoning. While many of these techniques are implemented at the prompting level or through chain-of-thought scaffolding, they suggest that self-reflection is a powerful tool for enhancing reasoning. Notably, these methods often induce substantial increases in generation length and latency, raising questions about the trade-off between deliberation and efficiency (Yang et al., 2025b; Yi & Wang, 2025; Chen et al., 2024; Team et al., 2025).

Related work further shows that RLVR can enhance reasoning performance by encouraging reflective behaviors through outcome-based feedback (Shah et al., 2025; Shinn et al., 2023; Wang et al., 2025; Xu et al., 2025). Empirically, models such as DeepSeek-R1 exhibit improved reasoning ability together with emergent self-reflective behaviors (Guo et al., 2025; Liu et al., 2025b). However, concurrent studies suggest that RLVR may primarily amplify latent capabilities already acquired during pretraining, rather than introducing fundamentally new ones (Shah et al., 2025; Yue et al., 2025). Our work complements this view by showing that self-reflection is a broadly distributed latent feature of LLMs, already encoded in hidden states even without explicit reflection training, and can be selectively enhanced or suppressed through simple vector interventions. This enables lightweight control of reflective behavior, including the mitigation of over-reflection, without additional training. While recent methods such as reflection-aware reinforcement learning explicitly optimize for self-reflection during training (Wan et al., 2025), we take a complementary mechanistic interpretability approach that studies and controls self-reflection directly through hidden-state steering.

3 Preliminary

3.1 Transformer Layer

Decoder-only transformers (Liu et al., 2018) map input tokens $\mathbf{t} = (t_1, t_2, \ldots, t_n) \in \mathcal{V}^n$ to output probability distributions over the vocabulary $\mathcal{V}$. Let $\mathbf{h}_i^{(\ell)} \in \mathbb{R}^d$ denote the residual stream activation (also referred to as the hidden state) of the i-th token at the ℓ-th layer, where d is the dimensionality of the hidden state. Each of the L transformer layers applies a sequence of attention and MLP transformations to update the residual stream:

$$\widetilde{\mathbf{h}}_i^{(\ell)} = \mathbf{h}_i^{(\ell)} + \text{Attn}^{(\ell)}(\mathbf{h}_{1:i}^{(\ell)}), \quad \mathbf{h}_i^{(\ell+1)} = \widetilde{\mathbf{h}}_i^{(\ell)} + \text{MLP}^{(\ell)}(\tilde{\mathbf{h}}_i^{(\ell)}). \tag{1}$$

The final hidden state is then projected to a probability distribution over the vocabulary $\mathcal{V}$ using an unembedding matrix followed by a softmax function.

3.2 Self-Reflection

Recent work has shown that large language models (LLMs), even when pretrained purely on next-token prediction, demonstrate surprising levels of reasoning ability (Mondorf & Plank, 2024; Liu et al., 2024b; Wang et al., 2023). However, this capability can be significantly enhanced through fine-tuning on reasoning tasks using either reinforcement learning with verifiable rewards (RLVR) or supervised learning with distilled responses from reasoning models trained from RLVR (Liu et al., 2025a; Wang et al., 2024; Zhao et al., 2025a). We denote the pretrained model as $\mathcal{A}_{\texttt{pt}}$, and its fine-tuned variant as $\mathcal{A}_{\texttt{ft}}$.

A notable emergent behavior observed in fine-tuned models $\mathcal{A}_{\texttt{ft}}$ is self-reflection—the model's ability to internally evaluate, critique, or revise its own reasoning process. Unlike standard reasoning, which involves generating a direct solution to a task, self-reflection introduces an intermediate meta-cognitive step where the model pauses or backtracks to reconsider its prior outputs. This behavior is often marked by explicit tokens such as "wait," which have been shown to correlate with improved reasoning outcomes (Li et al., 2024; Liu et al., 2025c; Yeo et al., 2025).

Importantly, self-reflection is not limited to any specific model architecture, observed across both proprietary models (Jaech et al., 2024) and open-source systems (Guo et al., 2025; OLMo et al., 2024; Yang et al., 2025a), indicating that it may be a general emergent property of optimizing for complex reasoning objectives. Although phrases such as "wait" are often treated as markers of self-reflection, recent work shows that a model may generate such expressions as superficial discourse patterns, without actually revising its prior reasoning (Wang et al., 2025). For this reason, we do not define self-reflection using a fixed set of tokens alone. Instead, we use an LLM-as-a-judge (Gu et al., 2024) to evaluate complete responses and determine whether they exhibit self-reflective behavior. When self-reflection is present, we further distinguish between responses that merely contain surface-level reflection and those that demonstrate genuine reconsideration of prior reasoning. This procedure allows us to move beyond token matching and obtain a broader grounded characterization of self-reflection. Further details are provided in Section 6.3.

4 Self-Reflection Already Emerges During Pretraining

In this section, we conduct a systematic analysis of self-reflection behavior in pretrained models $\mathcal{A}_{\texttt{pt}}$ and fine-tuned reasoning models $\mathcal{A}_{\texttt{ft}}$. Using the MATH500 dataset (Hendrycks et al., 2021) as our evaluation benchmark, we compare their reasoning trajectories. We first show that self-reflection emerges naturally in pretrained models, although it appears at a substantially lower frequency than in post-trained reasoning models. We then analyze hidden-state representations and find that even pretrained models implicitly encode and distinguish between self-reflective and non-self-reflective states, despite rarely expressing reflective behavior explicitly in their outputs.

4.1 Probing Self-Reflection in Pretrained Models

To investigate whether self-reflection emerges intrinsically in $\mathcal{A}_{\texttt{pt}}$, rather than being solely a byproduct of fine-tuning strategies such as RLVR, we examined the behavior of $\mathcal{A}_{\texttt{pt}}$ on mathematical reasoning tasks using

the MATH500 benchmark. Figure 1 (middle) highlights the contrast in self-reflection frequency between $\mathcal{A}_{\texttt{pt}}$ and $\mathcal{A}_{\texttt{ft}}$ models, alongside the clear geometric separation of their hidden states into reflection and non-reflection clusters. Remarkably, even in the absence of task-specific supervision, $\mathcal{A}_{\texttt{pt}}$ exhibited spontaneous self-reflective behavior in a small but non-negligible fraction of cases—approximately 0.6%. These instances are characterized by explicit reconsideration or revision of prior reasoning steps. For details on how we identify self-reflection instances, please see Section 6.3. While the self-reflection tokens differ somewhat from those typically observed in RLVR-trained models, their reflective nature is still discernible. These findings suggest that self-reflection is not solely acquired through fine-tuning, but rather emerges as a latent capability within the $\mathcal{A}_{\texttt{pt}}$, one that is infrequently activated but nonetheless present.

Reflection-Inducing Probing by Injecting CoT from $\mathcal{A}_{\texttt{ft}}$ into $\mathcal{A}_{\texttt{pt}}$ However, the extremely low frequency of self-reflection in $A_{\texttt{pt}}$ makes it challenging to analyze systematically and to develop methods (which will be studied in the next section) for controlling such behavior. To address this challenge, we propose a probing method, termed *reflection-inducing probing*, that isolates the model's capacity for self-reflection from its general reasoning ability. The key idea is to decouple reasoning competence from reflective behavior by inserting reasoning traces generated by the fine-tuned model $\mathcal{A}_{\texttt{ft}}$ into the input of the pretrained model $\mathcal{A}_{\texttt{pt}}$, and then measuring whether $\mathcal{A}_{\texttt{pt}}$ generates reflection in response.

Formally, given a question q, we use the fine-tuned model $\mathcal{A}_{\texttt{ft}}$ to generate a sequence of reasoning tokens:

$$\mathcal{A}_{\texttt{ft}}(q) = (\ \underbrace{r_1}_{\text{pre-reflection}}\ ,\ \underbrace{\texttt{reflection}}_{\text{explicit signal}},\ \underbrace{r_2}_{\text{post-reflection}}\ )$$

where r_1 denotes the initial chain-of-thought leading up to an explicit reflection token (e.g., "wait"), and r_2 represents the revised or continued reasoning after reflection. We then construct a new prompt by inserting r_1 (the pre-reflection reasoning) into the input of $\mathcal{A}_{\texttt{pt}}$, and evaluate whether $\mathcal{A}_{\texttt{pt}}$ independently produces a reflection token at the appropriate point. This setup ensures that both models operate on similar reasoning contexts, eliminating confounding differences in reasoning capability. By comparing the frequency and consistency of self-reflection under this controlled setting, we can more directly assess whether reflective behavior is present in the pretrained model and to what extent it is amplified by fine-tuning. The frequency of generating reflection with reflection-inducing probing is reported in Figure 1.

Self-Reflection emerges naturally in pretrained models albeit with much lower frequency Remarkably, $\mathcal{A}_{\texttt{pt}}$ exhibits clear self-reflective behavior in 38.9% of these cases—a dramatic increase from its baseline rate. This differential response demonstrates that while $\mathcal{A}_{\texttt{pt}}$ rarely produces overt reflection markers in standard contexts, it possesses latent self-reflection capabilities that can be activated by appropriate contextual triggers. These findings strongly suggest that self-reflection mechanisms are encoded during pre-training, rather than being exclusively developed through reinforcement learning. With 38.9% self-reflection cases, the subsequent section analyzes the hidden state representations underlying these self-reflective behaviors to provide further insights.

4.2 Hidden State Representations of Self-Reflection

To further investigate the emergence of self-reflection, we analyze the internal representations of the model when it decides to generate reflection versus when it does not. Specifically, we focus on the hidden states associated with reasoning tokens that immediately precede the generation of a reflection token (e.g., "wait"), and compare them to those that do not lead to reflection.

Since both the pretrained model $\mathcal{A}_{\texttt{pt}}$ and the fine-tuned one $\mathcal{A}_{\texttt{ft}}$ exhibit self-reflection behaviors, we use $\mathcal{A}$ to denote a generic model (either pretrained or fine-tuned), which will be specified in context. Given a question q, suppose the model $\mathcal{A}$ generates a sequence of reasoning tokens that includes self-reflection. Let $r = \mathcal{A}(q) = (r_1, \texttt{reflection}, r_2)$, where r_1 precedes the reflection token and r_2 follows it. Due to the auto-regressive nature of transformer models, the information from the question q and the reasoning tokens r_1 is aggregated into the hidden representation of the final token in r_1, which is then used by the last layer to predict the next token—the reflection token. For convenience, we refer to the final token in r_1 as a *reflection-inducing token (RIT)*, though its hidden state captures information from the entire preceding context (q, r_1).

Reflection-inducing tokens often coincide with sentence-final punctuation (e.g., ".", "!", or closing brackets) or specific markers such as "But". Now with a slight abuse of notation, let $h^{(\ell)}_{\text{reflection-inducing}}(q, r)$ denote the ℓ-th layer hidden state of a model at $\mathcal{A}$ corresponding to the reflection-inducing token. We collect all such hidden states from model outputs that contain reflection tokens into the following set

$$\mathbb{H}^{(\ell)}_{\texttt{reflect}} = \left\{ h^{(\ell)}_{\text{reflection-inducing}}(q, r) \in \mathbb{R}^d \right\}. \tag{2}$$

To study the properties of hidden states associated with self-reflection, we contrast this set with representations from cases where the model *does not* generate reflection. Specifically, to eliminate the confounding effect of token surface form, we extract hidden states from tokens that share the same form as reflection-inducing tokens (e.g., sentence-final punctuation), but which do not lead to self-reflection in the subsequent responses (within 20 tokens in the experiments). For notational convenience, we refer to these as *non-reflection-inducing tokens*, and denote their corresponding hidden states as $h^{(\ell)}_{\text{non-reflection-inducing (NIT)}}(q, r)$. We collect such non-reflection-inducing into the following set

$$\mathbb{H}^{(\ell)}_{\texttt{non-reflect}} = \left\{ h^{(\ell)}_{\text{non-reflection-inducing}}(q, r) \in \mathbb{R}^d \right\}. \tag{3}$$

This design ensures a fair comparison by controlling for the surface form of the reflection-inducing token, ensuring that any differences in hidden representations are attributable to the model's decision to reflect.

For $\mathcal{A}_{\texttt{pt}}$ models, which rarely generate self-reflective outputs, we use the method of reflection-inducing probing by injecting CoT from $\mathcal{A}_{\texttt{ft}}$ into $\mathcal{A}_{\texttt{pt}}$ to elicit reflective behavior. To visualize these high-dimensional representations, we employ principal component analysis (PCA) for dimensionality reduction, projecting the hidden states into a 2D space. Figure 1 presents the visualizations for the 15th layer (out of 28 total layers) for both models, with more layers presented in Appendix B.

Our analysis reveals a pattern: **both models show clear separation between self-reflection and nonself-reflection states**. While this separation is expected in $\mathcal{A}_{\texttt{ft}}$, which was explicitly trained to exhibit self-reflective behavior, the equally distinct clustering in $\mathcal{A}_{\texttt{pt}}$ is remarkable. Despite rarely generating explicit self-reflection tokens in its outputs, $\mathcal{A}_{\texttt{pt}}$ maintains internal representations that clearly distinguish between self-reflective and nonself-reflective contexts. This finding provides strong evidence that self-reflection capabilities develop during pretraining, with models encoding these patterns in their hidden state representations even when they rarely manifest in generated text. We will exploit this internal structure to develop methods for controlling self-reflection in the next section.

5 Controlling Self-Reflection in Language Models

In this section, we introduce our approach for identifying and manipulating self-reflection vectors in LLMs. Building on our finding in the last section that hidden representations distinctly separate self-reflective from non-reflective contexts, we construct self-reflection vectors, directions in activation space associated with self-reflective reasoning. We then demonstrate how these vectors can be used to bidirectionally control self-reflection behavior, either enhancing it to improve reasoning accuracy or suppressing it to reduce computational overhead. Through extensive evaluation across multiple mathematical reasoning benchmarks, we show that our method significantly outperforms strong baselines while offering flexible control over the performance-efficiency trade-off. Finally, we examine the cross-domain transferability of these vectors, revealing their potential as universal controls for self-reflection across diverse reasoning tasks.

5.1 Extract Self-Reflection Vectors

To identify the self-reflection vector in the residual stream activations, we compute the difference between the activations of self-reflective and nonself-reflective contexts. This technique, known as difference-in-means, effectively isolates key feature directions, as demonstrated in prior work (Rimsky et al., 2024; Arditi et al., 2024; Wu et al., 2025), motivating our application of this approach to the self-reflection domain. As in Section 4, we focus on the hidden state of reflection-inducing token, positing that this state encodes the model's transition into self-reflection reasoning.

Figure 2: Analysis of self-reflection vectors in DeepSeek-R1-1.5B. **Left**: cosine similarity between reflection vectors across datasets and their similarity to the "wait" token. **Middle**: Effect of steering strength α on performance and response length on MATH500 injected at layer 14. **Right:** Effect of injecting the self-reflection vector at different layers of DeepSeek-R1 1.5B ($\alpha = 0.03$) on Pass@1 and response length for MATH-500.

For each layer $\ell \in \{1, \ldots, L\}$, we compute the mean hidden states in the reflection set $\mathbb{H}^{(\ell)}_{\texttt{reflect}}$ and non-reflection set $\mathbb{H}^{(\ell)}_{\texttt{non-reflect}}$ as

$$\boldsymbol{\mu}^{(\ell)}_{\texttt{reflect}} = \text{mean}(\mathbb{H}^{(\ell)}_{\texttt{reflect}}), \quad \boldsymbol{\mu}^{(\ell)}_{\texttt{non-reflect}} = \text{mean}(\mathbb{H}^{(\ell)}_{\texttt{non-reflect}}), \tag{4}$$

and then construct the self-reflection vector as the difference-in-means vector

$$\boldsymbol{v}^{(\ell)} = \boldsymbol{\mu}^{(\ell)}_{\texttt{reflect}} - \boldsymbol{\mu}^{(\ell)}_{\texttt{non-reflect}}, \tag{5}$$

which captures both the direction along which self-reflective and nonself-reflective activations diverge, and the magnitude of that divergence.

5.2 Model Interventions for Controlling Trade-off between Reasoning and Efficiency

To actively modulate a model's tendency to reflect, motivated by the linear representation hypothesis and prior work (Arditi et al., 2024), we apply simple linear interventions based on the self-reflection vector $\boldsymbol{v}^{(\ell)}$ extracted from the ℓ-th layer, which is expected to capture the direction in representation space most associated with self-reflection. Specifically, we modify each residual stream $\boldsymbol{h}^{(\ell)}$ at the ℓ-th layer in (1) according to

$$\widehat{\boldsymbol{h}}^{(\ell)} = \boldsymbol{h}^{(\ell)} + \alpha \boldsymbol{v}^{(\ell)} \left\langle \boldsymbol{h}^{(\ell)}, \boldsymbol{v}^{(\ell)} \right\rangle, \tag{6}$$

where $\widehat{\boldsymbol{h}}^{(\ell)}$ then replaces $\boldsymbol{h}^{(\ell)}$ as the input to the next layer, and the scalar α controls the strength of the intervention. When $\alpha > 0$, the model's self-reflection behavior is enhanced; when $\alpha < 0$, it is suppressed. Setting $\alpha = 0$ disables the intervention, preserving the model's default behavior.

Ablation study on α To illustrate the effect of the linear intervention method for controlling self-reflection, we conduct an ablation study by varying the self-reflection steering strength α from -1.0 to 1.0, injecting the reflection vector at layer 14 in DeepSeek-R1-1.5B on the MATH-500 benchmark. The result is shown in Figure 2. Negative α values shorten responses, reducing average token length, while preserving accuracy. In contrast, positive α both lengthens responses, and boosts performance, peaking at $\alpha{=}0.03$ with a 12% performance gain in Pass@1, before declining at larger values due to over-reflection. This clear trade-off underscores α as a practical knob for balancing verbosity against reasoning depth. Further ablation detail on the effect of the injection layer is provided in Section 6.5.

5.3 Experimental Results

We evaluate our self-reflection control mechanism along three complementary dimensions: **reasoning ability**, **reasoning efficiency**, and **reasoning quality preservation**. For reasoning ability and efficiency,

Model	Method	MATH-500		AIME 2024		GPQA Diamond	
		Pass@1 ↑	LEN ↓	Pass@1 ↑	LEN ↓	Pass@1 ↑	LEN ↓
$\mathcal{A}_{\texttt{ft}}$ **Models**							
DeepSeek-R1-1.5B	Vanilla	84.1	4755	29.2	6118	14.0	4250
	BF	85.5	10122	30.0	8986	14.8	8210
	SR Enhanced	**87.4**	9458	**33.5**	8132	**18.9**	7496
	SR Suppressed	83.2	**3716**	27.3	**5229**	13.8	**3795**
DeepSeek-R1-7B	Vanilla	92.7	3585	55.8	4558	27.1	3696
	BF	93.1	7111	54.5	9629	32.0	5802
	SR Enhanced	**93.5**	8959	**58.2**	5684	**34.6**	6513
	SR Suppressed	91.2	**2439**	52.9	**3319**	26.5	**3120**
OLMo2-13B	Vanilla	41.8	3075	7.2	3753	15.2	2645
	BF	43.2	4891	10.2	4894	17.0	3714
	SR Enhanced	**47.9**	4574	**11.7**	4941	**19.1**	3490
	SR Suppressed	40.8	**2106**	6.5	**2656**	13.7	**1375**
OLMo3-7B-Think	Vanilla	94.5	7351	61.6	7212	47.6	8301
	BF	95.0	8251	62.3	9856	48.0	10543
	SR Enhanced	**95.4**	7690	**65.3**	9653	**51.2**	10015
	SR Suppressed	94.2	**4822**	61.3	**5201**	47.0	**5544**
$\mathcal{A}_{\texttt{pt}}$ **Models**							
Qwen2.5-1.5B	Vanilla	27.5 ± 1.3	$\mathbf{1515 \pm 242}$	0.2 ± 0.0	$\mathbf{544 \pm 98}$	5.7 ± 0.7	$\mathbf{702 \pm 40}$
	BF	29.6 ± 1.4	3993 ± 312	0.1 ± 0.2	4517 ± 428	5.0 ± 0.8	1389 ± 205
	SR Enhanced	$\mathbf{36.9 \pm 2.3}$	1836 ± 174	$\mathbf{6.1 \pm 1.7}$	2525 ± 233	$\mathbf{6.8 \pm 0.9}$	814 ± 96
Qwen2.5-7B	Vanilla	44.8 ± 1.9	$\mathbf{1294 \pm 0}$	3.9 ± 0.4	$\mathbf{2285 \pm 0}$	16.2 ± 0.6	$\mathbf{598 \pm 143}$
	BF	46.0 ± 1.1	3986 ± 351	5.3 ± 0.9	4526 ± 401	$\mathbf{16.9 \pm 1.2}$	1639 ± 188
	SR Enhanced	$\mathbf{56.6 \pm 2.7}$	2671 ± 214	$\mathbf{16.1 \pm 2.4}$	2941 ± 265	14.8 ± 1.5	1816 ± 203
Llama 3.1-8B	Vanilla	44.0 ± 2.4	$\mathbf{1613 \pm 189}$	3.5 ± 0.4	$\mathbf{1653 \pm 124}$	30.9 ± 1.2	$\mathbf{1914 \pm 351}$
	BF	40.1 ± 1.8	3771 ± 294	2.9 ± 0.8	3912 ± 377	26.1 ± 1.9	5031 ± 462
	SR Enhanced	$\mathbf{57.7 \pm 2.1}$	2887 ± 241	$\mathbf{16.5 \pm 2.6}$	2974 ± 286	$\mathbf{34.1 \pm 1.7}$	3995 ± 355

Table 1: Performance on mathematical and scientific reasoning benchmarks across $\mathcal{A}_{\texttt{ft}}$ and $\mathcal{A}_{\texttt{pt}}$ models. We compare **Vanilla** (no intervention), **BF** (budget forcing via "wait" token insertion), and our method **SR Enhanced/SR Suppressed** (applying positive or negative α to amplify or suppress self-reflection during inference). For $\mathcal{A}_{\texttt{pt}}$ models, we report only **SR Enhanced**, since self-reflection triggers it only rarely. Pass@1 denotes accuracy (higher is better), and LEN denotes average generation length (lower is better). We use 10% of the data as a validation set to select the optimal α in Eq. 6.

we report Pass@1 and average response length on two mathematical reasoning benchmarks, MATH-500 (Hendrycks et al., 2021) and AIME 2024, as well as one scientific QA benchmark, GPQA Diamond (Rein et al., 2024). To assess whether steering self-reflection alters the semantic quality of the reasoning process itself, we additionally evaluate the generated chains using ROSCOE-SS (Golovneva et al., 2023), which measures semantic agreement across reasoning steps using `facebook/roscoe-512-roberta-base` embeddings.

Experiments are conducted on both $\mathcal{A}_{\texttt{pt}}$ and $\mathcal{A}_{\texttt{ft}}$. For $\mathcal{A}_{\texttt{pt}}$ models, we use Qwen2.5-1.5B, Qwen2.5-7B and Llama 3.1 8B (Grattafiori et al., 2024; Yang et al., 2024). For $\mathcal{A}_{\texttt{ft}}$, we evaluate DeepSeek-R1 1.5B and 7B, OLMo-2-13B-Instruct and OLMo3-7B-Think (Guo et al., 2025; OLMo et al., 2024; Olmo et al., 2025). For $\mathcal{A}_{\texttt{pt}}$ models, we inject CoT traces from four different $\mathcal{A}_{\texttt{ft}}$ models separately. The table reports the mean and standard deviation over these four $\mathcal{A}_{\texttt{ft}}$ models.

We compare three inference strategies: **Vanilla**, which uses standard decoding without intervention; **BF** (Budget Forcing), which encourages reflection by appending a "wait" token to short generations (Guo et al., 2025; Muennighoff et al., 2025); and **SR Enhanced/SR Suppressed**, our method that perturbs hidden states using self-reflection vectors scaled by a coefficient α (positive for enhancement, negative for suppression). Since $\mathcal{A}_{\texttt{ft}}$ models can frequently trigger self-reflection, we evaluate both enhancement and suppression for them; in contrast, $\mathcal{A}_{\texttt{pt}}$ models exhibit such behavior only rarely, so we report SR enhancement only. We use 10% of the data as a validation set to select the optimal α in Eq. 6. Table 1 reports reasoning ability and

Setting	DeepSeek-R1-1.5B	DeepSeek-R1-7B	OLMo2-13B	OLMo3-7B-Think	Qwen2.5-1.5B	Qwen2.5-7B	Llama 3.1-8B
Vanilla	0.562	**0.589**	**0.537**	**0.594**	0.518	0.541	**0.576**
SR Enhanced	0.558	0.586	0.534	0.589	**0.523**	**0.549**	0.561
SR Suppressed	**0.565**	0.577	0.533	0.591	\	\	\

Table 2: ROSCOE-SS scores on MATH500 across all models. Higher is better. We compare **Vanilla** and our method **SR Enhanced/SR Suppressed**. For $\mathcal{A}_{\tt pt}$ models, we report only **SR Enhanced**, since self-reflection is triggered only rarely and suppression is therefore less informative.

efficiency, while Table 2 evaluates whether these interventions preserve the semantic quality of the reasoning chain.

Key Findings. Our results highlight four major insights. First, SR Enhancement improves reasoning performance across most evaluated datasets and model sizes. For example, Qwen2.5 7B's performance on MATH-500 jumps by 11.8 percentage points (from 44.8% to 56.6%), and DeepSeek-R1 variants enjoy similar boosts when employing reflection-enhanced decoding. Furthermore, this performance gain is also accompanied by a noticeable increase in response length, suggesting that longer responses can be beneficial when tackling more challenging reasoning tasks.

Second, SR Suppression offers fine-grained control over computational cost. It consistently reduces output length while preserving most of the model's accuracy. Notably, DeepSeek-R1-7B reduces average token length from 3585 to 2439 on MATH-500 with only a minor drop in Pass@1, which remains above 91%.

Third, these effects demonstrate strong generalizability across training paradigms and model families. The observed improvements hold for both $\mathcal{A}_{\tt ft}$ models (e.g., DeepSeek-R1, OLMO) and $\mathcal{A}_{\tt pt}$ models (e.g., Qwen2.5, Llama3.1), suggesting that the self-reflection signal is a robust and transferable mechanism that transcends specific architectures or fine-tuning methods.

Fourth, steering self-reflection does not materially degrade reasoning quality. Across model families, ROSCOE-SS scores remain broadly comparable to the vanilla setting, and in some cases even improve slightly, indicating that our intervention can modulate reflective behavior without compromising, and occasionally even enhancing, the semantic coherence of the reasoning chain.

Building on this generalizability, we emphasize the practical value of inference-time control over latent self-reflection dynamics. Unlike rigid interventions such as budget forcing, our method affords semantically grounded, continuous modulation of a model's internal self-reflection, enabling a tunable trade-off between performance and efficiency, especially in resource-constrained settings.

6 Further Analyses of Self-Reflection Vectors

6.1 Transferability of Self-Reflection Vectors

To investigate the transferability of self-reflection vectors across different reasoning domains, we evaluated whether vectors extracted from the GPQA Diamond dataset could be effectively transferred to mathematical reasoning tasks in MATH500. We compute the cosine similarity between self-reflection vectors extracted from different domains (MATH500 and GPQA Diamond), and between these vectors and the embedding of the token "wait" in DeepSeek-R1-Distill-Qwen-1.5B. For tokenizers containing multiple subword tokens for "wait", we report the average cosine similarity along with its variance. The results are plotted in Figure 2.

Model	Setting	PASS@1	Len
1.5B	SR Enhanced	86.4	7781
	SR Suppressed	82.6	3684
7B	SR Enhanced	93.0	6007
	SR Suppressed	91.0	2992

Table 3: Performance on MATH500 when applying self-reflection vectors extracted from GPQA Diamond to DeepSeek-R1 models.

Our analysis revealed remarkable consistency in the neural signatures of self-reflection across these distinct domains. Specifically, vectors extracted from GPQA and MATH500 exhibit high cosine similarity, suggesting that the internal representation of reflective states is largely domain-invariant. Notably, these self-reflection vectors are substantially different from the

Model	Onset Token	Evidence Quote
DeepSeek-R1-1.5B	`wait`	"Wait, that cannot be right because I double-counted ..."
DeepSeek-R1-7B	`wait`	"Wait, let me re-check the sign here ..."
OLMo2-13B	`But`	"But this step assumes independence, which is not valid ..."
OLMo3-7B-Think	`hold`	"Hold on, I should recompute from the definition ..."
Qwen2.5-1.5B	`wait`	"Wait, I need to verify whether the carry term is correct ..."
Qwen2.5-7B	`hmm`	"Hmm, that earlier conclusion does not follow from the equation ..."
Llama 3.1-8B	`wait`	"Wait, I made an invalid simplification in the previous step ..."

Table 5: Self-reflection examples for each model. For each model, we report one reflection token identified by the judge together with a short supporting quote from a response labeled as `GENUINE_SELF_REFLECTION`.

embedding of the token "wait", indicating that they encode deeper semantic properties of reflective behavior rather than surface-level cues.

Further, we evaluate the performance of self-reflection vectors derived from GPQA-Diamond on MATH500 using our proposed intervention method, SR-Enhanced/Suppressed, and present the results in Table 3. Notably, we observe similar performance gains to those seen with in-domain self-reflection vectors, as reported in Table 1. This cross-domain transfer demonstrates that the reflective mechanism captures a generalizable cognitive pattern rather than being confined to task-specific reasoning strategies. Together, these findings suggest that LLMs develop a unified internal representation of self-reflection, one that can be leveraged across tasks without the need for domain-specific fine-tuning.

6.2 Comparison of Different Methods

To validate our choice of the difference-in-means approach for generating steering vectors, we conduct a comparative analysis against alternative feature-extraction techniques. We consider four variants: (i) a difference-in-means direction with the projected update used in the main paper, (ii) a difference-in-means direction with additive steering, (iii) a standard PCA direction, and (iv) contrastive PCA (Abid et al., 2018). All methods are evaluated under identical intervention settings for both enhancing and suppressing self-reflection.

Table 4: Comparison of feature-extraction methods and steering methods for constructing the self-reflection vector on DeepSeek-R1 1.5B.

Method	SR Enhanced		SR Suppressed	
	PASS@1 ↑	LEN ↓	PASS@1 ↑	LEN ↓
Difference-in-means	**87.4**	**9458**	**83.2**	**3716**
↪ Additive Steering	86.0	9845	83.0	3639
PCA	84.3	10074	79.1	3912
Contrastive PCA	84.7	9876	80.6	4078

The evaluation was performed under identical intervention settings for both the enhancement and suppression of the target behavior. The quantitative results are shown in Table 4. The data indicate that the difference-in-means approach achieves the highest task performance in both intervention scenarios, yielding superior PASS@1 scores while maintaining reasonable vector lengths.

This empirical finding aligns with insights from recent work in mechanistic interpretability (Wu et al., 2025). These studies suggest that for the specific goal of causal steering of model behavior, simple directional vectors derived from differences often outperform other techniques, thereby motivating our choice of the difference-in-means approach.

6.3 Identifying Self-Reflection Instances

To identify self-reflection in language model outputs, we use an LLM-as-a-judge procedure instead of relying solely on a fixed set of keywords. We define a response as exhibiting genuine self-reflection only when the model explicitly revisits its earlier reasoning and performs a meaningful check, correction, backtrack, revision, or re-derivation. This criterion is intentionally stricter than keyword matching: discourse markers

such as `wait`, `hold on`, or `let me think` are not considered sufficient unless they are followed by substantive reconsideration of prior reasoning.

Given a question-response pair, the judge assigns one of three labels: `NO_REFLECTION`, `SURFACE_REFLECTION`, or `GENUINE_SELF_REFLECTION`. For responses labeled as `GENUINE_SELF_REFLECTION`, the judge further identifies all self-reflection occurrences in the response. For each occurrence, the judge returns (i) the reflection phrase, (ii) the corresponding reflection token, and (iii) a short evidence quote. This allows us to recover the full set of self-reflection points within a generation, rather than restricting analysis to only the first reflective turn. The full judge prompt is provided in Appendix C.

We apply this procedure to model outputs on the MATH500 benchmark, using a maximum generation length of 8196 tokens. Final labels and self-reflection tokens are determined by the judge rather than by the presence of any single keyword. To provide qualitative intuition, Table 5 presents one representative example for each model, together with a reflection token identified by the judge and a short supporting quote. As a complementary analysis, we also examine the surface tokens associated with self-reflection in Table 6. We find that the specific tokens are not identical across models, but they exhibit substantial overlap. In particular, markers such as `wait`, and

Model	Top-5 Reflection Onset Tokens
DeepSeek-R1-1.5B	`wait`, `but`, `hold`, `hmm`, `actually`
DeepSeek-R1-7B	`wait`, `but`, `hold`, `so`, `actually`
OLMo2-13B	`but`, `wait`, `however`, `hold`, `actually`
OLMo3-7B-Think	`hold`, `wait`, `but`, `hmm`, `actually`
Qwen2.5-1.5B	`wait`, `hmm`, `but`, `hold`, `actually`
Qwen2.5-7B	`hmm`, `wait`, `but`, `actually`, `hold`
Llama 3.1-8B	`wait`, `but`, `hold`, `actually`, `hmm`

Table 6: Top-5 most frequent reflection onset tokens for each model, as identified by the judge on responses labeled `GENUINE_SELF_REFLECTION`.

`actually` recur across multiple model families, suggesting that genuine reflective revision is often expressed through a partially shared set of surface cues, despite model-specific variation.

6.4 Linear Separability of Self-Reflection States

To quantify whether self-reflection states are linearly encoded in model representations, we train a linear SVM at each layer to distinguish reflection-inducing tokens from non–reflection-inducing tokens in Qwen2.5-1.5B and DeepSeek-R1-Distill-Qwen-1.5B. The classifier is trained on 10% of the hidden states and evaluated on the remaining 90%.

As shown in Figure 3, test accuracy exceeds 99% across all layers for both models. This result indicates that reflection-inducing and non–reflection-inducing tokens are almost perfectly linearly separable in the original hidden-state space, suggesting that self-reflection is represented as a robust latent direction rather than a weak or diffuse signal.

Notably, this linear structure also appears in Qwen2.5-1.5B, which produces very few explicit self-reflection tokens. This finding supports our claim that self-reflection is encoded internally even in models that rarely express it overtly, and is therefore not tied only to surface markers or a specific training recipe.

Figure 3: Linear-probe test accuracy of a linear SVM trained to distinguish reflection-inducing tokens from non–reflection-inducing tokens at each layer of DeepSeek-R1-Distill-Qwen-1.5B and Qwen2.5-1.5B. Accuracy exceeds 99% across all layers for both models, indicating near-perfect linear separability.

This linear separability also helps explain the effectiveness of our steering method: the intervention acts along an existing representational axis that already distinguishes reflective from non-reflective states, allowing it to amplify or suppress self-reflection by leveraging an emergent internal structure. Complementary PCA visualizations in Appendix B provide a qualitative view of the same geometric pattern.

6.5   Ablation Study

We determine the injection configuration using a two-stage selection procedure. First, for each candidate layer ℓ, we conduct a grid search over the steering coefficient $\alpha \in [-1.0, 1.0]$ to identify the value that yields the best validation performance. This search covers both positive and negative directions, corresponding respectively to enhancing and suppressing self-reflective behavior. Second, after identifying effective scales, we compare candidate injection layers to determine where the model is most receptive to intervention.

Ablation on Steering Strength α. We first examine the effect of steering magnitude by varying α from -1.0 to 1.0 while fixing the injection layer to layer 14 of DeepSeek-R1-1.5B. The results are shown in Figure 2. Overall, the relationship between α and performance is clearly asymmetric: moderate positive values are beneficial, whereas overly large magnitudes in either direction are harmful.

For negative α, the intervention suppresses the self-reflection direction. In this regime, response length decreases substantially, indicating reduced deliberative reasoning. Notably, moderate negative values shorten outputs without causing a large drop in Pass@1, suggesting that part of the model's reflective behavior may be verbose rather than essential.

For positive α, the model is pushed further along the self-reflection direction. Small positive values improve Pass@1 and generally increase response length, indicating that stronger reflective reasoning can help the model revise faulty intermediate steps. However, this benefit is not monotonic. Performance peaks around $\alpha = 0.03$, after which larger positive values begin to hurt both answer quality and efficiency. Taken together, these results suggest that self-reflection is most useful when it is moderately amplified rather than maximized.

Effect of Injection Layer. We then isolate the role of layer choice by fixing $\alpha = 0.03$ and injecting the self-reflection vector at each layer of DeepSeek-R1-1.5B on MATH-500 (Figure 2). We observe a clear layer dependence: performance improves most strongly when the intervention is applied at middle layers, with layer 14 giving the best overall result.

This pattern suggests that self-reflection is most effectively modulated at intermediate stages of computation. When injected into early layers, the steering signal has to pass through many subsequent transformations, which can dilute or overwrite its effect before it influences the final reasoning trajectory. As a result, early-layer interventions produce only limited gains. In contrast, injecting into very late layers places the perturbation close to token generation, where it is less able to reshape the latent reasoning process and more likely to act as a superficial bias on next-token prediction.

The strong performance of middle-layer injection is consistent with the view that these layers encode higher-level reasoning dynamics in a form that is both semantically meaningful and still causally effective for downstream computation (Jiang et al., 2025; Skean et al., 2025). Intervening at this stage allows the model to revise or strengthen its internal reflective process before the final answer is produced.

7   Conclusion

In this paper, we demonstrated that self-reflection in large language models is an emergent capability that develops during pretraining rather than being uniquely induced by reinforcement learning techniques. Through contrastive analysis of hidden state representations, we revealed that even models with minimal explicit reflection behavior maintain internal neural signatures that distinguish self-reflective contexts. By exploiting these representations, we developed an intervention method that enables bidirectional control over self-reflection, providing a flexible mechanism to navigate the performance-efficiency trade-off without requiring additional training. This work primarily focuses on understanding the internal representations underlying self-reflection and leveraging them for controllable behavior. There remain several important directions for future work. For instance, our current approach requires users to specify in advance whether self-reflection should be enhanced or suppressed, rather than allowing the model to adapt automatically to task demands. In addition, it relies on access to internal activations, which may not be available in closed-source or API-based settings. It will be of interest to develop adaptive reflection control and extend the approach to more restricted model access scenarios, but we leave thorough investigation as future work.

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A Implementation Details

For the $\mathcal{A}_{\mathtt{ft}}$ models, we adopted a specialized prompting strategy that incorporates the explicit token `<think>` to elicit self-reflective reasoning and promote internal deliberation.

In contrast, for the $\mathcal{A}_{\mathtt{pt}}$ models, we employed the same prompt template but omitted the `<think>` token. This design allowed us to isolate and assess the specific influence of `<think>` on eliciting reflective behaviors and its downstream impact, as Qwen models do not natively rely on such explicit triggers.

Unless otherwise noted, we set the maximum generation length to 32,784 tokens to support complex multi-step reasoning and avoid premature truncation. All experiments were conducted on a computing cluster equipped with 8 NVIDIA A5000 GPUs.

B PCA Visualization of Self-Reflection States

To complement the quantitative linear-probe results in the main text, we apply PCA to hidden states extracted from Qwen2.5-1.5B and DeepSeek-R1-Distill-Qwen-1.5B. Figure 1 shows the PCA projection of the 15th-layer representations, while Figures 4 and 5 provide additional layer-wise visualizations for both models.

Across layers, reflection-inducing and non–reflection-inducing tokens form two elongated clusters that become increasingly separated along the first principal component. In very early layers there is still some overlap, but from middle layers onward a clear margin emerges, and by the deepest layers the two groups are well separated in both model families.

These PCA visualizations are consistent with the linear-probe results reported in the main text, providing a low-dimensional illustration of the same underlying geometric structure: self-reflection corresponds to a direction in representation space that becomes progressively more organized across depth.

C LLM Judge Prompt for Identifying Self-Reflection

Prompt for identifying self-reflection instances

```
You are evaluating whether a model response exhibits genuine self-reflection.

Definition:
Genuine self-reflection means that the model explicitly reconsiders, questions, checks,
backtracks on, or revises its earlier reasoning.  This must go beyond superficial discourse
markers such as "wait", "hold on", or "let me think".  A response counts as genuine
self-reflection only if there is evidence that the model revisits prior reasoning and
meaningfully changes, re-evaluates, or re-derives it.

Label the response as one of:
- NO_REFLECTION: no reflective behavior
- SURFACE_REFLECTION: contains reflection-like phrases, but no substantive reconsideration of
prior reasoning
- GENUINE_SELF_REFLECTION: explicitly revisits prior reasoning and meaningfully re-evaluates,
revises, or corrects it

Instructions:
1.  Read the full question and full response.
2.  Focus on behavior, not keywords alone.
3.  Do not classify as genuine self-reflection unless the response refers back to earlier
reasoning and performs a meaningful check, correction, backtrack, or revision.
4.  Prefer precision over recall.
5.  If the response is labeled as GENUINE_SELF_REFLECTION, identify all reflection occurrences
in the response, not just the first one.
```

```
6.  For each reflection occurrence, return the reflection phrase, the corresponding reflection
token, and a short evidence quote.
7.  If there is no genuine self-reflection, return an empty list for "reflection_instances".

Return JSON only:
{
"label":  "NO_REFLECTION | SURFACE_REFLECTION | GENUINE_SELF_REFLECTION",
"confidence":  0.0--1.0,
"reflection_instances":  [
{
"reflection_phrase":  "...",
"reflection_token":  "...",
"evidence_quote":  "..."
}
]
}

Question:
{question}

Response:
{response}
```

Figure 4: PCA visualization of hidden states from the Qwen2.5-1.5B model across 14 layers.

Figure 5: PCA visualization of hidden states from the DeepSeek-R1-Distill-Qwen-1.5B model across 14 layers.