Awakening LLMs' Potential: A Two-Stage Pipeline to Mitigate Confirm Biases

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Abstract

Large language models (LLMs) are increasingly trained to abstain on difficult questions. However, they often misuse this ability: they output *Unknown* despite being potentially able to solve the questions, or they fail to understand why questions are truly unsolvable. We formalize this mismatch between potential ability and inclinations of *abstention* as the *Confirm Biases* phenomenon. We introduce WAKENLLM, a two-stage pipeline that (1) Extracts corresponding *Confirm Biases* samples, and (2) Measures how many of them can be converted to correct predictions. Experiments suggest that LLMs can achieve up to a 68.53% accuracy gain on *Confirm Biases* samples. Through the pipeline, we offer model-selection strategies in multi-stage workflows. Further, we study the phenomenon influences varying from models families and parameter sizes, and dive deeper into root causes. Finally, by comparing WAKENLLM with other baselines, we measure how effectively each framework elicit LLMs' potential, pointing to future perception-aware LLM development. Code and datasets are in https://anonymous.4open.science/r/WakenLLM-toolkit-018B.

1 Introduction

LLMs like GPT and Qwen series have shown superior performance on benchmarks like BIG-Bench, MMLU, and GSM8K (Brown et al., 2020; OpenAI et al., 2024a; Chowdhery et al., 2022; Srivastava et al., 2023; Hendrycks et al., 2021; Hessel et al., 2022). In addition to question-answering performances, more attention is paid to the trustworthiness LLM development (Gao et al., 2024; Bubeck et al., 2023). For example, solving *Knowledge Boundary* problems can help LLMs to know when to answer and when to abstain (Li et al., 2025b; Wen et al., 2024). However, most prior work focuses on whether and when LLMs should refuse to answer. In contrast, we ask a complementary yet opposite question: Are there situations that LLMs abstain too early, despite being capable of solving the questions? If so, inclinations towards *abstention* would harm LLMs' performances.

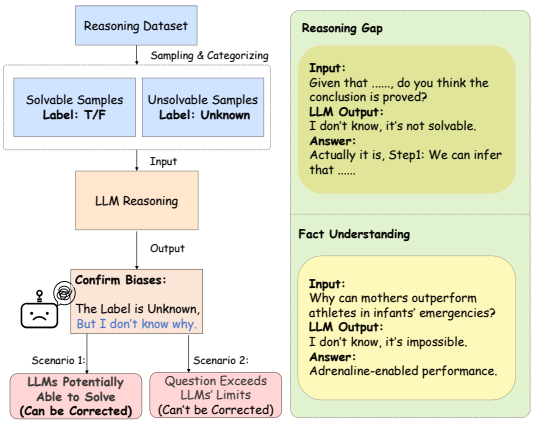


Figure 1: Definition of *Confirm Biases*: Samples LLMs abstain on, but can be potentially corrected. We attribute this phenomenon to two representative causes: *Fact Understanding* and *Reasoning Gap*—highlighting 1. Limited ability to logically solve problems. 2. Limited understanding of facts (Right), which will be addressed in Section 6.6.

We define this as the *Confirm Biases* phenomenon, and dive into questions with *Unknown* labels. There are two possible situations regarding samples LLMs abstain on: (1) Problems that are objectively unsolvable, or (2) LLMs subjectively consider the problems unsolvable. Since LLMs' potential ability, despite outputting *Unknown*, remains less-studied, understanding how LLMs express uncertainty and the potential of overcoming this phenomenon can be rather important for trustworthiness and reliable LLM development.

To fill this gap, we propose WAKENLLM, a two-stage pipeline to mitigate the *Confirm Biases* phenomenon, yielding substantial improvements in accuracy across eight LLMs, which further proves that LLMs' label-prediction abilities is harmed by inclinations of *abstention*.

Based on the pipeline, as models perform differently at different stages, we also offer model-selection strategies in multi-stage workflows. For models families and parameter sizes, we also carry out different experiments: (1) *Conformity*: Unlike prior work (Weng et al., 2025) stating LLMs with larger sizes show lighter conformity effects, we discover this is also related to the label types: models with larger sizes conform less to *True&False* labels, but more conform to *Unknown* labels; Meanwhile, we test Conformity by inputting reasoning traces LLMs generated, and ask LLMs to reflect on them, results suggest that this serves mainly as misguidance rather than help. (2) *Degradation*: for *Confirm Biases* samples, through our pipeline processing, the smaller LLMs are more inclined to output *True&False* labels rather than *Unknown*; whereas larger ones perform exactly the opposite. These findings can complement prior research.

Further, we dive deeper to explore root causes of the *Confirm Biases* phenomenon, which exposes problems of LLMs to be solved. Finally, we compare our pipeline with existing baselines, to quantify the LLMs' potential elicited by these frameworks. Our work offers value for future LLM trustworthiness development. To summarize, our contributions are fourfold:

▷ **We formulate the *Confirm Biases* phenomenon**, where models choose to abstain despite having the potential to solve questions correctly, or failed to understand why questions are truly unsolvable. Such biased behavior can seriously influence LLMs' performances.

▷ **We propose WAKENLLM**, a two-stage pipeline that extract the *Confirm Biases* samples, and measures how many of them can be converted to correct predictions. Based on the pipeline, **we offer LLM selection strategies in multi-stage workflows**, as models perform dramatically different at specific sequences.

▷ **We carry out *Conformity* and *Degradation* experiments**, and analyze LLMs biases resulting from model families and parameter sizes. The experimental findings can complement prior research.

▷ **We dive in to the root causes of the *Confirm Biases* phenomenon**, and point out problems remain to be solved in the future. By comparing WAKENLLM with existing baselines, **we measure how effectively each framework elicits LLMs' potential**. Our work offers a new perspective on future perception-aware LLMs development.

2 Related Work

Abstention Behavior Abstention behavior (e.g., outputting Unknown) has been increasingly studied as a mechanism to reduce hallucinations and improve reliability of LLMs (Wen et al., 2025). Beyond conceptual discussions, recent benchmarks (Muhamed et al., 2025) evaluate abstention across different query types, such as unspecified questions and ambiguous inputs. These studies show that even state-of-the-art models still struggle to determine when to abstain.

Earlier work like (Rajpurkar et al., 2018) contains questions with no correct options. Recent benchmark like (Kirichenko et al., 2025) evaluates models ability to abstain under various scenarios, which is a step forward in granularity and profession. However, these work remain limited, as they mainly focus on evaluating the outcome, rather than studying how this happen and how to mitigate this.

LLM Trustworthiness & Biases Prior work mitigate LLM hallucinations by introducing the concept of *Knowledge Boundary*, which encourages models to recognize when a question lies beyond their limits (Wen et al., 2024). Other work measures the *internal confidence* to assess outputs (Kadavath et al., 2022). However, these studies mainly focus on uncertainty and reliability evaluation, while the biases of abstention remain largely unexplored.

Regarding biases of abstention, research is mainly about sensitivity of social problems, like race (Khorramrouz and Levy, 2025), or malicious ones like hate speech (Im et al., 2026). However, abstention biases on difficult problems is less-studied. Since *Difficulty* is a subjective factor, different models show different biases.

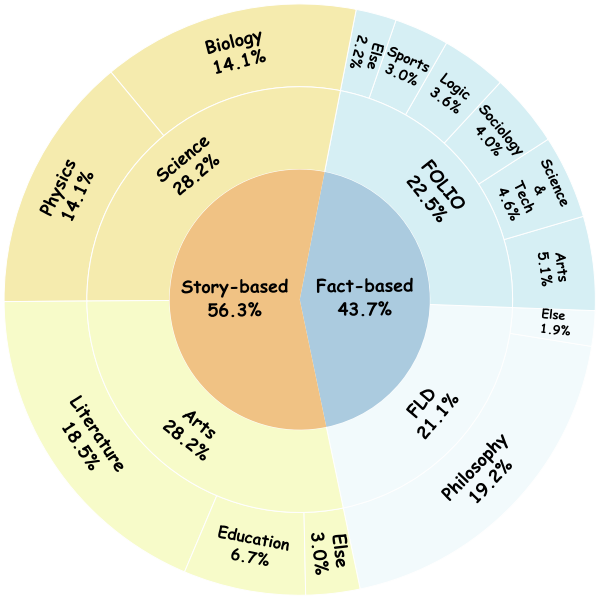
Stage-wise Pipelines Early work like self-consistency (Wang et al., 2023) generate multiple reasoning traces, and get the majority answer as the output. Later in Agentic systems, Reflexion (Shinn et al., 2023) propose a feedback-reflection system, which allows models to learn from mistakes.

However, there is no specific pipeline for evaluating and mitigating *Confirm Biases* phenomenon, i.e., a multi-stage pipeline for triggering LLMs' potential is less-studied, but urgently needed. A detailed related work is in Appendix A.

3 Datasets Composition

To explore the effects of the *Confirm Biases* phenomenon on different label types, we classify sam-

Figure 2: Overall dataset distribution, with samples grouped into two forms: **story-based** (56.3%) and **fact-based** (43.7%). Details of topics ("Else" category included) is in Appendix C.



ples into two category: (1) *solvable samples*, where problems have *True/False* labels that can be objectively solved; and (2) *unsolvable samples*, which are labeled *Unknown* and objectively can not be solved. Furthermore, as in Figure 2, to better understand how different text styles influence, we categorize datasets as follows:

Fact-based Datasets The information in contexts is stated atomically, like "A is X, B is Y". **FLD** (Morishita et al., 2024) supplies three kinds of sample labels annotated as *True*, *False*, or *Unknown*. We randomly sample 600 samples: 300 solvable (*True/False*) and 300 unsolvable *Unknown* ones. And we draw 640 samples—320 solvable samples with *True/False* labels and 320 *Unknown* samples from **FOLIO** (Han et al., 2024), which also has the same three-way labeling.

Story-based Datasets The contexts are long passages, more aligned with humans' reading habits. We extract samples from four fields: *Physics*, *Biology*, *Figurative-language* and *Writing-strategies* from ScienceQA (Lu et al., 2022), and applied the same sampling strategy. The former two are categorized as Science datasets, the latter two are Arts datasets. Dataset details are in Appendix C.

4 Proposed Pipeline: WakenLLM

As in Figure 3. Our pipeline first extracts *Confirm Biases* samples, later the two-stage stimulation is implemented to elicit model's potential on these samples. For **Vanilla Setting**, the stage 1 deals with the extracted samples, and the stage 2 receives falsely answered samples from stage 1, we inform LLMs that they solved problems incorrectly, and validate whether such stimulation can trigger their potential for correctness. From this pipeline, we can get the percentage of *Confirm Biases* samples that can be corrected by LLMs. For **Remind-then-Guide (RtG)** settings, we either include wrong labels, or previous reasoning traces in the prompt. We examine whether LLMs would conform to these extra guidance after being stimulated.

Table 1: Information of datasets used in experiments.

Dataset	Samples	Form	Writing	Source
FLD	600	**Conclusion**	Abstract	Gen
FOLIO	640	**Conclusion**	Plain	Real
Science	800	**Q&A**	Plain	Real
Arts	800	**Q&A**	Plain	Real

4.1 Samples Extraction

Our pipeline begins with label-prediction on *Story-based* and *Fact-based* datasets, we acquire tasks accuracy and extract corresponding *Confirm Biases* samples—where LLMs output *unknown* when samples are solvable, or fail to explain why samples are truly unsolvable. Since this is performed separately for each model, *Confirm Biases* samples differs from each too.

4.2 Vanilla Setting

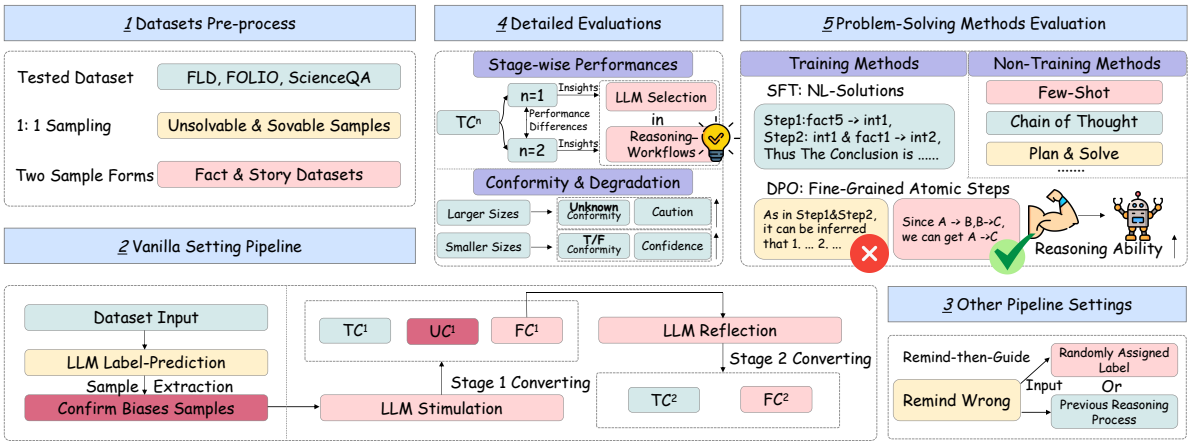
After extracting *Confirm Biases* samples, we input them into stage 1. The outputs fall into three categories: (1) LLMs output correct labels under stimulation, called **True Converting (TC)**. (2) output incorrect *T/F* labels for *solvable* samples, denoted as **False Converting (FC)**. (3) fail to comprehend and remain output *Unknown* for *solvable* samples, which is **Unknown Converting (UC)**. We use **UCR**, **FCR**, and **TCR** to represent **rates of each type converting.**, and define them as:

$$TC_t^n = \sum_{y_t \in D_{\text{VP}}^n} \mathbb{1}\big(\hat{y}_t^n = y_t\big), \quad TCR_t^n = \frac{|TC_t^n|}{|D_{\text{VP}}^n|} \tag{1}$$

$$FC_t^n = \sum_{y_t \in D_{\text{VP}}^n} \mathbb{1}\big(\hat{y}_t^n \neq y_t\big) \tag{2}$$

$$UC_t^n = \sum_{y_t \in D_{\text{VP}}^n} \mathbb{1}\big(\hat{y}_t^n \in U,\ y_t \notin U\big) \tag{3}$$

Figure 3: Overview of our work. We begin with Fact and Story-based datasets, sampling from solvable samples (True&False labels) and unsolvable samples (Unknown labels) at 1 : 1 ratio. Then we (1) extract corresponding *Confirm Biases* samples, and (2) Applies a two-stage pipeline: stage 1 uses stimulation to rerun extracted samples, while stage 2 gathers the remaining *False Converting* samples from stage 1 for further potential awakening.



In the above equations, $t \in \{s, u\}$ denotes sample types (solvable or unsolvable), and $n \in \{1, 2\}$ indicates the stimulation stages. D^n_{VP} represents the input of *Confirm Biases* samples in the n-th stage. First stage input D^1_{VP} was extracted from the input datasets. For the second stage, we collect the **False Converting** samples as the input, from which we can obtain: $D^2_{\text{VP}} = FC^1$.

Omitting superscripts like TCR_s represent the sum of results from stage 1 and 2, and TCR^1 denotes the converting rate of both sample forms in the first stage. To be specific, $TCR_s = TCR^1_s + TCR^2_s$, standing for the TCR value of solvable samples in both stages; Likewise, $TCR^1 = TCR^1_s + TCR^1_u$, indicating TCR for stage 1 that sums up both solvable and unsolvable samples.

To study LLMs' hidden potential, we define **Overall Converting Rate (OCR)** as follows:

$$OCR = \frac{|TC^1 \cup TC^2|}{|D_{\text{vp}}|} \tag{4}$$

OCR refers to the portion of *Confirm Biases* samples that are eventually corrected by LLMs. By calculating this, we can obtain the potential accuracy harmed by inclinations of *abstention*.

4.3 Remind-then-Guide (RtG) Setting

Label Conformity We test how LLMs display conformity facing *Confirm Biases* samples. We firstly inform LLMs of inputting *Confirm Biases* samples, then provide wrong labels to test whether such reminding then misguiding affects outputs. We compare TCR changes with and without the RtG setting, and average results on two stages:

$$Conf_t = \frac{1}{2}(\underbrace{TCR^1_t - TCR^{1'}_t}_{\text{Stage 1 Conformity}} + \underbrace{TCR^2_t - TCR^{2'}_t}_{\text{Stage 2 Conformity}}) \tag{5}$$

As indicated in Section 4.2, the subscript t represents two sample types s or u, separating conformity analysis on solvable and unsolvable samples. $TCR^{1\prime}_t$, $TCR^{2\prime}_t$ indicates True Converting Rate (TCR) in two stages given all assigned labels are different from ground-truth labels.

Reasoning Traces (RT) Conformity We also examine whether LLMs, after being reminded of previous mistakes, can reflect on previous reasoning traces to avoid making same mistakes. To the best of our knowledge, we are the first to test *Conformity* on reasoning traces. The two stages of Reasoning Influence is denoted as RI^1 and RI^2.

Reasoning Influence in Stage 1 Including LLMs' reasoning traces in prompts, and we rerun stage 1 to assess its stability. Similarly, RI^1 is calculated by changes of converting rate with and without reasoning traces. Values below zero indicates that previous reasoning traces are misguiding and thus results in declined accuracy, while above zero suggests this can help guide models.

Reasoning Influence in Stage 2 Similarly, we save reasoning traces of FC^1 samples in stage 1, and run stage 2 by including them in prompts. We remind LLMs these reasoning may contains flaws since the samples come from the FC^1. RI^2 accesses whether LLMs can better reflect on their

Table 2: Comparison of eight LLMs across four datasets (FLD, FOLIO, Science, Arts), grouped by evaluation settings. **RP** refers to reasoning process under Remind-then-Guide setting. The highest value is in bold per column.

Model	Dataset	Vanilla			RtG (Label)		RtG (RT)	
		TCR[1]	TCR[2]	OCR	Conf$_u$	Conf$_s$	RI^1	RI^2
GPT-3.5	FLD	12.61	14.43	25.22	3.33	**64.25**	10.84	-12.30
	FOLIO	14.41	42.10	50.44	31.97	16.81	-6.30	-42.10
	Science	21.05	3.33	21.63	1.96	19.22	0.59	-3.33
	Arts	26.04	4.00	27.10	-3.88	14.24	3.12	0.00
GPT-4o	FLD	18.88	28.19	41.65	37.38	8.17	-6.48	-23.50
	FOLIO	37.34	44.40	65.16	51.90	9.63	0.00	-44.77
	Science	24.73	7.76	28.96	4.58	11.74	-3.68	-7.16
	Arts	18.60	8.24	24.17	23.31	8.07	1.14	-8.24
GPT-o4-mini	FLD	11.52	10.23	13.67	3.33	6.35	5.29	-5.97
	FOLIO	14.04	0.00	14.04	1.83	8.77	-6.30	-12.02
	Science	15.66	0.00	15.66	1.66	12.94	0.86	-10.24
	Arts	57.66	44.44	61.26	0.00	50.13	5.12	-43.02
LLaMA-3.1-8B	FLD	41.97	26.03	48.90	11.04	50.04	1.09	-18.56
	FOLIO	45.86	11.40	50.84	13.61	38.73	5.52	-3.07
	Science	45.94	5.95	50.61	51.44	38.60	12.91	-5.95
	Arts	24.26	8.57	25.75	9.02	30.99	11.30	-4.77
LLaMA-3.1-405B	FLD	20.65	**53.73**	41.50	**57.63**	9.35	-17.66	-48.28
	FOLIO	28.76	29.92	49.22	23.01	6.11	0.00	-17.69
	Science	32.85	2.50	33.03	18.50	9.02	0.71	0.19
	Arts	4.40	0.00	4.40	28.91	0.81	-0.77	0.00
Qwen-2.5-7B	FLD	**48.31**	40.00	**68.53**	42.34	22.06	-5.61	-31.67
	FOLIO	19.73	36.84	47.36	38.71	4.92	14.48	-36.84
	Science	15.83	10.00	24.08	0.00	55.21	14.59	-2.98
	Arts	29.34	25.37	36.44	7.20	43.39	8.47	-13.27
Qwen-2.5-72B	FLD	48.20	9.80	51.21	9.14	33.08	1.21	-9.80
	FOLIO	31.51	11.37	38.36	2.20	10.65	-1.37	-6.82
	Science	10.81	3.12	11.20	22.07	33.42	-0.38	0.00
	Arts	25.00	9.76	25.56	24.12	12.52	-1.95	0.00
Deepseek-R1	FLD	33.93	50.00	37.50	0.83	3.34	-3.44	-10.99
	FOLIO	28.21	25.00	35.90	0.00	6.22	0.00	-17.95
	Science	12.33	0.00	12.33	4.58	8.75	-3.68	0.87
	Arts	46.88	14.29	53.12	3.33	5.78	0.00	-23.12

reasoning, is calculated by the changes of converting rate with and without reasoning traces.

$$RI^1 = \frac{|TC^1| - |TC^{1\prime\prime}|}{|D^1_{VP}|} \quad (6)$$

$$RI^2 = \frac{|TC^2| - |TC^{2\prime\prime}|}{|D^2_{VP}|} \quad (7)$$

$TC^{1\prime\prime}, TC^{2\prime\prime}$ are obtained with previous reasoning traces included in prompts.

Detailed summary of all used metrics is available in Appendix Table 7.

5 Experiments

Our experiment covers following models: GPT-3.5, GPT-4o (OpenAI et al., 2024b) and o4-mini; LLaMA-3.1 series (Touvron et al., 2023), Qwen-2.5 series (Bai et al., 2023) and Deepseek-R1 (Guo et al., 2025).

The stimulation style design considers different characteristics of two datasets forms: (1) **Concise Stimulation**: Basic error notifications without correction guidance, and (2) **Detailed Stimulation**: Detailed error notifications with structural and step-by-step guidance. For Fact-based ones, which LLMs are less trained on, providing *Detailed Stimulation* can enhance performance; For Story-based ones, the information is embedded in long stories, which LLMs are largely trained on, providing *Detailed Stimulation* can induce hallucinations (Huang et al., 2025). Experiments of different stimulation styles are in Section 6.4.

We set Temperatures of all tested models to 0.5, except for 1.0 in Ablation Study. For results evaluation, we apply a two-step output verification: the output answering is first examined for specific keywords matching. When this fails, GPT-4o (Temperature=0.0) is deployed as a LLM judge.

5.1 Results on the Vanilla Setting

As shown in Table 2, we report detailed experimental results, including three metrics addressed before: True Converting Rate (TCR) for both stages, and Overall Converting Rate (OCR). The LLaMA and Qwen series show superior OCR on small-parameter series, whereas the GPT series shows the opposite trend. We infer that, in general, higher parameter sizes correlate with lower OCR, i.e., larger models are show less potential of correction on *Confirm Biases* samples.

One possible explanation is that larger models

tend to exhibit higher confidence, as in (Kadavath et al., 2022). This may lead to coherent outputs on *Confirm Biases* samples, resulting in lower *OCR*.

We consider the two-stage pipeline sufficient for analyzing LLMs potential. As the input to Stage 2 (FC^1) contains fewer samples, adding more rounds would result in *Diminishing Marginal Returns*.

5.2 Results on the RtG Setting

RtG settings contain two modes: Label and Reasoning Traces (RT) Conformity: We remind LLMs that they incorrectly predicted the sample before, then add randomly assigned labels, or previous reasoning traces. A wrap-up of findings can be found in Appendix L. During our experiment, we adjust rates of assigned wrong labels at four given probabilities (100%, 66.7%, 50%, 0%). Detailed Remind-then-Guide conformity tests are available in the Table 9, 10, 11, 12 and Appendix H.

Label Conformity Judging from Table 2, we observe that even when LLMs are reminded of their previous incorrect answers, they still demonstrate a strong tendency towards conformity. One key influencing factor appears to be the **Parameter Sizes**: models with smaller parameter sizes, such as GPT-3.5 and LLaMA-3.1-8B, are more easily misled on samples with *True&False* labels. In contrast, larger models such as GPT-4o and LLaMA-3.1-405B, strongly conform to the *Unknown* labels. Meanwhile, Qwen series show similar yet mild features, it may be attributed to smaller parameters gap compared to other model families.

We believe this can also be attributed to training bias. Larger models are trained on broader and more diverse corpora, which may expose them to a wider range of rare or atypical scenarios (e.g., Unknown labels). Combined with the effects of Knowledge Boundary awareness and abstention behavior, it is reasonable that larger models demonstrate greater caution, as alignment training may encourage conservative responses under uncertainty.

Reasoning Trace (RT) Conformity We input previous reasoning traces and require LLMs to reflect on this. However, results on both RI^1 and RI^2 reveal that previous reasoning traces are unstable, it is more serious for RI^2 than RI^1. Changes in accuracy result from the divergence in how problems are solved at different times. Notably, for *Unknown* labeled samples, reasoning traces tend to be more unreliable — reflecting on them typically leads to a higher accuracy drop. This proves the ability of LLMs to step-by-step express uncertainty is weak.

This exposes a serious issue: For LLM-annotation datasets with reasoning traces, there can be problems and needs for manual verifications. We attribute this to the nature of Reinforcement Learning, where the training paradigm is result-oriented, leaving intermediate steps flawed and problematic.

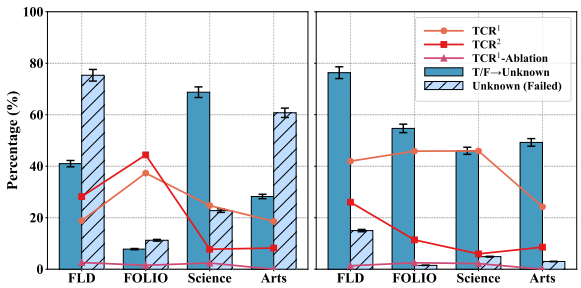


Figure 4: Percentage of GPT-4o (left) and LLaMA-3.1-8B (Right) exhibit *Confirm Biases*. "T/F→Unknown" indicates solvable samples are predicted as "*Unknown*". "Unknown (Failed)" denotes cases predicted as "*Unknown*" because of limited understandings.

6 Detailed Analysis

6.1 TCR Analysis & Takeaways

As shown in the line chart of Figure 4, we observe clear divergences between TCR^1 and TCR^2 across different datasets. This indicates that many wrongly-predicted samples in stage 1 can be corrected in stage 2. In contrast, Story-based TCR^1 shows a substantially lower TCR^2, whereas LLaMA-3.1-8B demonstrates much higher TCR^1. Noticeably, as in Figure 2, for Reasoning Models like o4-mini and Deepseek-R1, they perform bad on stage 2, as some values of TCR^2 is zero.

We introduce **model-selection strategies for multi-stage workflows**: (i) For GPT-4o, when facing *Fact-based* datasets, we can place the model at a latter order, since stage 2 offers a huge accuracy gain; However, for *Story-based* datasets, the improvement of stage 2 accuracy is limited, so being placed in the front should be better. (ii) For LLaMA-3.1-8B, it is better to "do it right the first time", as being placed in the front always leads to better performance. Details are in Appendix L.4.

6.2 Confirm Biases Phenomenon

As LLMs' abilities differ, we first quantify the percentage of samples that models show *Confirm Biases* on. Bar charts in blue in Fig 4 demonstrate the

percentage of samples that GPT-4o and LLaMA-3.1-8b showing this phenomenon, while complete results for all models are in Table 8.

We conclude that **the *Confirm Biases* phenomenon is prevalent across LLMs**. For GPT-4o, FOLIO exhibits a relatively lower percentage. For *FLD* and *Arts* datasets, LLMs exhibit greater variability in understanding why samples are labeled as *unknown*; In contrast, LLMs face challenges on the *Science Dataset*: For LLaMA-3.1-8B, there is a rise in the percentage in solvable samples predicted as *unknown*, but the ability to comprehend *unknown* labeled samples is much worse.

6.3 Ablation Study

From the stage 1 output, we isolate the Unknown Converting samples (UR^1)–those LLMs have *abstained* on twice, and re-input them back to stage 1 stimulation. Both LLaMA-3.1-8b and GPT-4o are set with 1.0 temperature to ensure dynamicity.

As Figure 4 shows, more than 95% of label-prediction remain unchanged. This demonstrates that *Confirm Biases* is largely immune to repeated n-shot prompting; Consequently, any effective correction must rely on a further stage 2 rather than reiterating stage 1, and adjusting temperature alone offers limited gain. Since higher Temperature adjusts the probability distributions of output token to be more even, which is still limited within the candidate answers.

6.4 Stimulating Styles Comparison

As in Section 5, based on different styles of corpora, we apply different stimulation styles to different datasets. To evaluate the effectiveness, we swapped the two styles of stimulation within our pipeline, with GPT-4o as the base model. As shown in Table 3, **switching stimulation styles leads to a drop in TCR^1_s**, indicating weakened understanding of samples with *T/F* labels. In contrast, TCR^1_u increases for unknown-labeled samples. Although the overall converting rate (OCR) improves, this gain is unstable, as TCR^1_s remains more consistent. **Reliability** indicates the results are more reliable based on higher TCR^1_s.

Furthermore, we observe a trade-off: as the label-prediction ability on solvable samples declines, the model becomes better at unsolvable ones. We argue that because human feedback is subjectively evaluated across different providers, alignment training (e.g., RLHF) can imprint preferences into models, and such balance is hard to reach.

Table 3: Converting rate regarding different stimulating methods *CS*, *DS* refer to *concise* and *detailed Stimulation*. Rows shaded gray are used in our pipeline. Higher values of TCR^1_s are associated with better Reliability.

Metrics(%)	TCR^1	TCR^1_s	TCR^1_u	Reliability
FLD (CS)	37.27	10.65	26.62	↓
FLD (DS)	18.88	**13.64**	5.24	↑
Arts (CS)	18.60	**16.06**	2.54	↑
Arts (DS)	22.54	14.65	7.89	↓

6.5 Baseline Comparisons

We primarily analyze the "awakening ability" regarding *Confirm Biases* samples being answered correctly based on TC^1 and TC^2 samples, and this is denoted as LLMs' "Potential Ability". We combine with the "Explicit Ability" *Acc(Direct)*, as in Section 4.1, our pipeline starts with LLM reasoning on four datasets, acquiring the corresponding accuracy *Acc(Direct)* and extracting *Confirm Biases* samples. By adding "Potential" and "Explicit" accuracy together, we gain the LLMs' potential ability can be achieved without training. Here, *D* represents the complete dataset, as we calculate the proportion of TC^1 and TC^2 samples over the whole dataset to acquire the accuracy.

$$\text{Acc(WAKENLLM)} = \underbrace{\text{Acc(Direct)}}_{\text{Explicit Ability}} + \underbrace{\frac{|TC^1 \cup TC^2|}{|D|}}_{\text{Potential Ability}} \tag{8}$$

Our goal is not to outperform baselines under more favorable conditions, instead to measure how effectively different frameworks elicit LLM potential. As in the line chart in Figure 5, most mainstream baselines exhibit substantial performance gaps compared to WAKENLLM, indicating current frameworks are far from eliciting LLMs' full potential, pointing to future perception-aware LLM development. Details are in Table 6.

6.6 Phenomenon Exploration

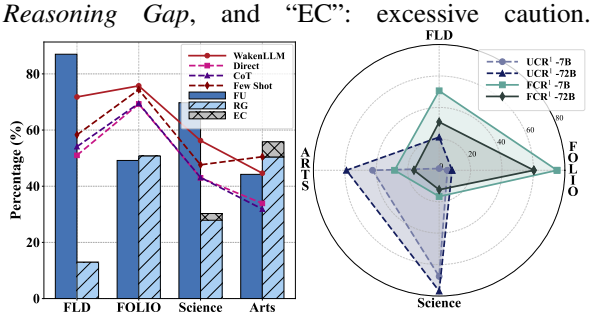
To explore root causes of *Confirm Biases*, we deploy GPT-4o as an LLM judge (Temperature=0.0) to identify problems based on their reasoning traces, problems mainly fall into three categories:

▷ **Fact Understanding (FU)** – LLMs do not comprehend facts in the passage.

▷ **Reasoning Gap (RG)** – LLMs fail to perform logical operations that reach the hypothesis.

▷ **Excessive Caution (EC)** – LLMs demonstrate cautiousness over outputting their answering.

Figure 5: Reasons of *Confirm Biases* samples for GPT-4o (left). Qwen-2.5-7B and 72B False and Unexcited Converting Rate (FCR, UCR) comparison (Right). "FU": *Fact Understanding*, "RG": *Reasoning Gap*, and "EC": excessive caution.



Root Causes of Phenomenon As in the bar chart of Figure 5, EC is a minor cause compared to FU and RG. Our experiments reveal that root causes LLMs inclined to output *Unknown* contain both objective and subjective reasons. For the former part, FU and RG represent whether LLMs can understand given facts, or successfully inference based on comprehension, which are the main reasons; for EC, the inner biases, is a minor problem that only occurs in *Story-based* datasets. We attribute this to the complexity of *Story-based* samples: long stories in **Arts** highlight comprehension requirements.

6.7 Degradation Analysis

In the stage 2 of WAKENLLM pipeline, we don't exclude the possibility that incorrectly predicted samples FC^1 from stage 1 may be further converted to *unknown* in stage 2, which should be denoted as UC^2. It is reasonable that LLMs initially generate incorrect answers, but in the later stage choose to abstain. We elaborate this as below:

$$Deg = \frac{\left|FC^1 \setminus \left(FC^2 \cup TC^2\right)\right|}{\left|FC^1\right|} \quad (9)$$

As shown in Table 4, GPT-4o achieves higher TCR^2 among all datasets than GPT-3.5. And problems regarding *Degradation* can be minor, since only GPT-4o demonstrates serious effects on Science dataset. Coupled with higher *Deg*, this suggests that when facing problems LLMs previously answered incorrectly—especially those beyond their ability—GPT-4o tends to output *Unknown*. In contrast, GPT-3.5 is much mo re likely to provide an incorrect answer instead of admitting uncertainty.

This is further proved by experiments of *UCR* and *FCR* for Qwen-7b and 72b. The formulas are addressed in Appendix F. We compare the output of the Qwen-2.5 series (7B and 72B model), as shown in radar-chart in Figure 5: (1) Results show uniform label-prediction distributions: For FLD and FOLIO, LLMs are more willing to output True or False incorrectly instead of Unknown; However, for **Story-based datasets**, LLMs show the opposite tendency. (2) The larger the parameter sizes, the more likely the models are to output *Unknown*.

This complements (Kadavath et al., 2022), which states larger models show higher confidence: On one hand, larger models can output *Unknown* confidently, which meets their claim. On the other hand, they show cautiousness towards abstention because of the inclinations of outputting *Unknown*. Considering this, future research on LLMs empirical phenomenons can be carried out in a more fine-grained level, e.g., combining both the attributes of labels and LLMs' biases.

Table 4: Degradation Analysis of GPT-4o and GPT-3.5. Exceptionally high *Deg* values of GPT-4o is in bold.

Models	**GPT-4o**		**GPT-3.5**	
Metrics(%)	**TCR^2**	**Deg**	**TCR^2**	**Deg**
FLD	28.19	3.08	14.43	3.09
FOLIO	44.40	5.22	42.10	6.32
Science	7.76	**26.86**	3.33	3.33
Arts	8.24	1.13	4.00	0.00

7 Conclusion

In this work, we formulate the *Confirm Biases* phenomenon: the inclinations of LLMs outputting *unknown* despite being potentially able to solve input questions, and such *abstention* behavior strongly influence LLM performances. We present WAKENLLM, a two-stage pipeline for evaluating and mitigating the *Confirm Biases* phenomenon. Our pipeline elicits LLMs' potential ability, offering high accuracy gain among tested datasets. Experiments show that while LLMs give up and answer *unknown* on the first try, our pipeline can stimulate them to answer correctly. These insights suggest evaluation metrics that value LLMs' ability beyond one-shot performances. By carrying out *Conformity* and *Degradation* experiments, we better understand LLM behaviors vary from model families and parameter sizes. Although huge leaps in LLM architectures may be limited in the near future, our findings suggest that existing baselines remain far from eliciting LLMs' full potential, paving the way for future perception-aware LLM development.

Limitations

Even though our work has helped elicit LLMs' reasoning potential, our final metrics are calculated with respect to output labels, and producing the correct label while providing a flawed reasoning chain is common and remains an open problem for better reinforcement learning approaches in the future. How to fundamentally quantify their true ability with true reasoning process remains a problem in the future. Besides, specifying whether the output *Unknown* is due to understanding the unverifiable elements or inability to fully comprehend still remains a problem, currently we just clarify demands within prompts.

Ethical Considerations

Our research utilizes publicly available datasets (FLD, FOLIO and ScienceQA) containing synthetic and artificial reasoning samples without personal information. We acknowledge potential biases in our SFT and DPO training processes and implement atomic reasoning criteria to ensure fair evaluation. All training scripts, evaluation code, and prompt templates are made available for reproducibility. We focus on improving reasoning quality rather than enabling harmful applications. Our work adheres to academic integrity standards and contributes to responsible AI development through more interpretable reasoning.

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A Related Work Details

Multi-Step Reasoning CoT (Wei et al., 2023) first showed that furnishing step-wise exemplars markedly improves LLM performance on arithmetic and commonsense problems. Follow-up work refines this paradigm: *scratchpads* (Nye et al., 2021), *least-to-most prompting* (Zhou et al., 2023), and *self-consistency* (Wang et al., 2023). More recently, multi-agent and symbolic reasoning approaches like *multiagent debate* (Du et al., 2023), *symbolic chain-of-thought* (Xu et al., 2024), and neurosymbolic reasoning with logic provers (Olausson et al., 2023) further strengthen factuality and logical consistency.

Iterative Self-Refinement and Critique Self-Refine (Madaan et al., 2023) establishes a generate–criticise–rewrite loop. Ambiguity handling and uncertainty decomposition are also explored: *AmbigQA* (Min et al., 2020), *Decomposing Uncertainty* (Hou et al., 2024), and rank-based calibration (Huang et al., 2024).

Logical Inference Classic benchmarks like (Clark et al., 2019), (Rajpurkar et al., 2018), (Thorne et al., 2018), and (Yang et al., 2018) stress-test fact verification, ambiguity, and multi-hop reasoning. Meanwhile, multilingual and cross-domain robustness is increasingly crucial for real-world deployment. Recent work such as (Li et al., 2025a) highlights the importance of handling multilingual heterogeneity and collaborative anomaly detection across diverse social media environments.

Active Prompting Active-Prompt (Diao et al., 2024) selects informative exemplars to boost performance under budget constraints. Meanwhile, Ling et al. (2025) denotes different prompt coverage leads to various effects.

B Baseline Details

In this section, we run multiple reasoning frameworks that help improve downstream tasks of LLM reasoning. By comparing our proposed pipeline with existing baselines, we can further prove that current frameworks are far from eliciting LLMs' full potential. Detailed templates and examples can be found in Appendix N.

Chain-of-Thought (CoT) The CoT prompting method guides large language models (LLMs) to generate intermediate reasoning steps before producing a final answer. It improves multi-step reasoning performance by making the inference process explicit. This technique is particularly effective in arithmetic and logic-heavy tasks, as shown in prior works such as Wei et al. (2023).

Few-shot Few-shot prompting involves presenting the model with a few annotated examples in the input to demonstrate the task format. It enables in-context learning without any gradient updates. Despite its simplicity, few-shot prompting serves as a strong baseline in many LLM applications (Brown et al., 2020).

Tree-of-Thought (ToT) Tree-of-Thought extends the CoT framework by exploring multiple reasoning paths in a tree structure and evaluating intermediate steps. It mimics a planning process that considers alternative possibilities, significantly enhancing reasoning robustness and allowing backtracking or reevaluation of incorrect paths (Yao et al., 2023).

Plan & Solve Plan-and-Solve separates the reasoning process into two stages: first planning a high-level outline or decomposition of the task, then solving sub-tasks based on that plan. This two-stage strategy enhances controllability a in reasoning, and has shown strong performance across complex benchmarks (Wang et al., 2023).

Supervised Fine-Tuning (SFT) Supervised Fine-Tuning (SFT) is the standard method for aligning LLMs by training on curated human-annotated question-answer pairs. Unlike prompt-only methods, SFT optimizes the model weights directly through gradient updates to produce desirable outputs. It forms the foundation of instruction-tuned models like InstructGPT and serves as a widely-used supervised baseline for alignment tasks (Ouyang et al., 2022). The common consensus is that SFT provides the essential starting point for alignment, but by itself is insufficient to fully capture complex human preferences, often requiring further preference optimization or reinforcement learning. The optimized formula is below:

$$\mathcal{L}_{\text{SFT}}(\theta) = -\sum_{i=1}^{N} \log \pi_\theta(y_i \mid x_i),$$

Direct Preference Optimization (DPO) Direct Preference Optimization (DPO) is a reinforcement learning-free approach that fine-tunes LLMs using preference data. Given pairs of outputs (e.g., preferred vs. dispreferred), DPO directly optimizes

Table 5: Comparison of different LLM reasoning–guidance frameworks. WAKENLLM integrates all eight dimensions as the first holistic solution for diagnosing and mitigating the *Confirm Biases* phenomenon. For used symbols, ✓: Fully covered, ●: Partially covered, ✗: Not covered. Detailed Related Work section can be found in Appendix A.

Paradigm	Guidance	Questioning	Stimulation	Dynamic Samples Selection	Reflection	Stage-wise Examining	Fine-Grained Decomposing	Diversity
CoT (Wei et al., 2023)	✓	✗	✗	✗	✗	✗	✗	✗
ToT (Yao et al., 2023)	✓	✓	✗	●	●	✓	✓	✓
Faithful-CoT (Lyu et al., 2023)	✓	✓	✓	✗	✗	✓	✗	✓
Plan&Solve (Wang et al., 2023)	✓	✗	●	✗	✗	✓	✓	✗
Self-Refine (Madaan et al., 2023)	✓	✗	✓	✗	✓	✓	✗	✓
Reflexion (Shinn et al., 2023)	✓	✗	✓	✗	✓	✓	✗	✓
Decomposed Prompting (Khot et al., 2023)	✓	✓	✗	✗	✗	✗	✓	✗
Active Prompt (Diao et al., 2024)	✓	✗	✓	✓	✗	✗	✗	✓
CoTAL (Cohn et al., 2025)	✓	✗	✓	✓	✗	✓	✗	✗
Cochain (Zhao et al., 2026)	✓	✓	✗	✓	✗	✓	✓	✓
Trace-of-Thought (McDonald and Emami, 2025)	✓	✓	✗	✗	✗	✓	✓	✗
MAPS (de Souza Loureiro et al., 2025)	✓	✗	✓	●	✓	✓	✗	✓
CoD (Xu et al., 2025)	✓	✗	✗	✗	✗	✓	✗	✗
ReSearch (Chen et al., 2025)	✓	✓	✗	✓	✓	✓	✓	✗
WAKENLLM (Ours)	✓	✓	✓	✓	✓	✓	✓	✓

the log-likelihood ratio between them, providing alignment benefits similar to reinforcement learning methods like PPO while avoiding their instability and complexity (Rafailov et al., 2024). The common consensus is that DPO offers a simpler and more stable alternative to reinforcement learning-based methods, making it a practical choice for preference alignment, though it may still struggle with capturing nuanced or long-term user preferences. The formula can be concluded as below:

$$\mathcal{L}_{\text{DPO}}(\theta) = -\mathbb{E}_{(x,y^+,y^-)}\Big[\log\sigma\Big(\beta\big(\log\frac{\pi_\theta(y^+|x)}{\pi_{\text{ref}}(y^+|x)} - \log\frac{\pi_\theta(y^-|x)}{\pi_{\text{ref}}(y^-|x)}\big)\Big)\Big]$$

Self-Reflection Self-reflection has been widely adopted as a strategy for improving LLM reasoning by prompting the model to critique and refine its own initial answer. However, this paradigm implicitly assumes that the model can (i) detect flaws in its original reasoning, (ii) identify missing or contradictory evidence, and (iii) reliably revise its conclusion. Prior work shows that these assumptions rarely hold in practice: when the initial reasoning is misguided, the reflection stage often reproduces the same errors, leading to self-confirming loops rather than genuine correction. In addition, self-reflection primarily operates on the model's *final* answer, without addressing perception-level uncertainty or the model's tendency to prematurely output **Unknown**.

B.1 Experiment Setup Details

We choose four LLMs: GPT-4o, GPT-3.5, LLaMA-3.1-8B and Qwen-2.5-7B for our detailed baseline experiments. We categorize our baseline methods into two kinds: training and non-training, in order to see whether the *Confirm Biases* phenomenon can be solved with or without parameter revision. For model training and open-source model deployment, the experiments ran on four Tesla V100-SXM2-32GB GPUs.

B.2 Training Methods Details

As explained before in Appendix B.1, we elaborate our facilities and setup for training. In this section, we demonstrate our details for the training.

For SFT (Supervised Fine-Tuning), we extract 1,000 training samples from exactly same dataset, the prompt instruction can be found in Appendix N.

For DPO (Direct Preference Optimization), we apply LLM Judge to help select the reasoning process with many atomic steps as possible. This includes two parts: (1) Prompt Template that includes task guiding details (e.g., definition of atom steps) and task instructions (2) Testing cases that can perfectly prove and verify which response is better given the metrics and requirements. All information above can be found in Appendix N.

C Datasets Details

FLD Following Morishita et al. (2024), **FLD** is a fully synthetic benchmark for multi-step logical inference. Formal proof chains of depth 0–15 are automatically generated and then verbalized into natural-language premises plus a hypothesis. Each instance is labeled **Proved**, **Disproved**, or **Unknown**, making the dataset ideal for assessing whether a model can (i) draw correct conclusions and (ii) abstain when evidence is insufficient.

FOLIO **FOLIO** (Han et al., 2024) contains **1,430** human-written first-order-logic stories that

Model	Methods	Accuracy (%)			
		FLD	FOLIO	Science	Arts
GPT-3.5	Direct	50.17	40.63	44.63	29.25
	CoT	49.67	42.34	44.13	31.00
	Few-shot	49.67	37.50	43.75	33.88
	Tree-of-Thought	33.50	43.91	36.00	28.25
	Plan & Solve	42.83	45.47	33.63	26.38
	Self-Reflection	56.67	42.50	42.00	34.00
	WAKENLLM(ours)	**60.26**	**46.68**	**48.38**	**35.04**
GPT-4o	Direct	51.00	69.53	43.00	33.88
	CoT	54.10	69.53	43.12	31.87
	Few-shot	58.30	74.40	47.62	**50.50**
	Tree-of-Thought	52.83	70.62	43.38	29.25
	Plan & Solve	52.17	69.84	42.38	30.25
	Self-Reflection	55.33	69.37	37.50	34.50
	WAKENLLM(ours)	**71.79**	**75.74**	**56.25**	44.64
LLaMA-3.1-8B	Direct	39.17	51.56	49.50	47.50
	CoT	40.67	51.88	46.50	43.25
	Few-shot	33.33	51.25	48.25	39.13
	Tree-of-Thought	38.33	47.66	40.63	30.00
	Plan & Solve	35.50	52.81	38.75	26.75
	Self-Reflection	51.33	51.88	47.25	44.00
	SFT	49.17	50.47	46.50	49.12
	DPO	50.33	48.60	48.50	49.62
	WAKENLLM(ours)	**61.50**	**65.47**	**62.72**	**53.43**
Qwen-2.5-7B	Direct	41.83	57.81	44.12	47.12
	CoT	43.83	60.62	42.75	46.62
	Few-shot	44.50	58.75	38.00	42.25
	Tree-of-Thought	39.83	57.19	37.88	45.88
	Plan & Solve	40.67	56.88	37.62	39.62
	Self-Reflection	48.67	63.75	39.50	39.00
	SFT	48.67	57.34	**49.62**	43.12
	DPO	**49.33**	54.21	48.38	44.13
	WAKENLLM(ours)	48.06	**65.55**	47.56	**54.37**

Table 6: Accuracy comparison of multiple baselines for four LLMs evaluated on four datasets. Each block represents a distinct model series. The highest accuracy is marked black.

bridge everyday commonsense with formal theorem proving. Every narrative provides its gold logical forms and a hypothesis whose truth value (**True**, **False**, or **Unknown**) is automatically certified. The official split is 1 001/226/203 for train/dev/test, offering fewer but richer problems than FLD and requiring explicit refusals when the passage leaves the hypothesis undecided.

ScienceQA **ScienceQA** (Lu et al., 2022) is a multi-modal multiple-choice benchmark with **21,208** elementary- and middle-school questions across 26 topics. To create an abstention setting comparable to the logic corpora, we select questions from Physics and Biology (science) as well as Writing-Strategies and Figurative-Language (arts). For 50% of the chosen items we delete two random supporting sentences with GPT-4o, then manually verify that no unique answer remains; these items are re-labeled **Unknown**.

Fields/Domains Analysis Our comprehensive dataset consists of four distinct collections, each representing different domains of logical reasoning. The **FLD (First-Order Logic Dataset)** contains 600 samples across 11 topics, with Philosophy being the dominant subject (545 samples, 90.8%), followed by Logic (37 samples, 6.2%), and 9 other topics with minimal representation. The **FOLIO dataset** comprises 640 samples distributed across 7 topics, including Arts (146 samples, 22.8%), Science & Technology (130 samples, 20.3%), Sociology (114 samples, 17.8%), Logic (102 samples, 15.9%), Sports (85 samples, 13.3%), Geography (39 samples, 6.1%), and Architecture (24 samples, 3.8%). The **ScienceQA dataset** contains 800 sam-

Table 7: Detailed listing of all metrics used among different experimental settings in our work. Metrics within different settings or systems are separated by dashed lines. RT stands for reasoning traces included within the setting. $f \in \{s, u\}$ indicates whether the sample types belong to *solvable* or *unsolvable*. $n \in \{1, 2\}$ indicates the stage of processing. **Omitting subscripts indicates all sample types; omitting superscripts indicates all two stage considered.** Detailed calculations can be found in Appendix F.

Vanilla Settings	Definition	Rationality/Motivation
True Converting (TC)	TC_t^n represents samples converted to **correct** labels.	Measuring LLMs' true potential under stimulation.
True Converting Rate (TCR)	TCR_t^n is the **percentage** of TC_t^n.	Calculate the percentage of LLMs' potential of solving problems after stimulation.
False Converting (FC)	FC_t^n represents samples converted to **incorrect** labels.	Under stimulation, problems LLMs are stimulated to produce wrong answers instead of giving up.
False Converting Rate (FCR)	FCR_t^n is the **percentage** of FC_t^n.	Research the inclination of LLMs outputting wrong answer over **abstention** (answering incorrectly).
Unknown Converting (UC)	UC_t^n represents samples converted to **unknown** samples.	To confirm that the samples are too hard for LLMs to reason.
Unknown Converting Rate (UCR)	UCR_t^n is the **percentage** of UC_t^n.	Research the inclination of LLMs **abstention** (answering unknown) over outputting wrong answer.
Overall Converting Rate (OCR)	After two stage stimulation, the percentage of *Confirm Biases* samples are converted to TC, sum of TCR^1 and TCR^2.	Potential part of samples LLMs can reason correctly, but did wrong because of **abstention**.
Remind-then Guide (Label&RT)	**Definition**	**Rationality/Motivation**
Label Conformity	LLMs exhibit distinct tendency of conformity on solvable and unsolvable labels, denoted as $Conf_t$.	Research how conformity biases are enlarged facing different label forms.
Reasoning Guidance (RI^1)	Taking the previous reasoning trace as input, to determine whether performance is better or worse with reflection.	LLM training based on RL is result-oriented, leaving the reasoning trace flawed and biased.
Reasoning Guidance RI^2)	Based on original output, LLMs should rethink the problem, this is to define whether the reasoning trace is consistent.	As the stability of reasoning is important, ensuring the consistency of reasoning can be important.
Other Experiments	**Definition**	**Rationality/Motivation**
Degradation (Deg)	In stage 2 stimulation, the input FC^2 may be degraded and output unknown, which should be denoted as UC^2.	Consideration for randomness and instability of LLMs output. Better make up for the pipeline.

ples evenly split between Biology and Physics (400 samples each, 50%). Finally, the **Arts dataset** includes 800 samples with Literature as the primary topic (526 samples, 65.8%), followed by Education (190 samples, 23.8%), Philosophy (77 samples, 9.6%), Linguistics (4 samples, 0.5%), and Psychology (3 samples, 0.4%).

The dataset distribution reveals a hierarchical structure: at the top level, we distinguish between **Fact-based reasoning** (43.66%) and **Story-based**

reasoning (56.34%). The four major categories are distributed as follows: FLD (21.13%), FOLIO (22.53%), Science (28.17%), and Arts (28.17%). This balanced distribution ensures comprehensive coverage of different reasoning paradigms, from formal logical reasoning in FLD to narrative-based reasoning in Arts, providing a robust foundation for training and evaluating logical reasoning capabilities across diverse domains.

Unknown Label Annotation For the first **FLD** and **FOLIO**, the *Unknown* label is originally included in their annotations. For SCIENCEQA, we randomly select half of the samples and employ GPT-4o to randomly delete two sentences from the given facts. We then re-label these modified samples as *Unknown*. Additionally, we perform **manual verification** to ensure that relabeled samples are semantically consistent with assigned labels, which are objectively unverifiable.

Search-Based Planning Frameworks Instead of generating a single chain, **Tree-of-Thought (ToT)** views partial solutions as nodes in a tree and performs breadth-first search with value heuristics (Yao et al., 2023). **Decomposed Prompting** turns a complex task into callable sub-prompts that can be solved independently (Khot et al., 2023).

D Metrics Details

As shown in Table 7, we elaborate all used metrics in our experiment, along with the motivation of designing them. A solid and comprehensive evaluation system offers contributions to LLM reasoning.

E LLM Usage Statement

GPT-4o, Claude-3-7 and Grok 3 are used for code organizing and paper framing.

F Formula Details

In the main body of paper, we highly focus on True Converting (TC) flow that LLMs are able to convert *Confirm Biases* samples to predict correct labels. In this section we explain False Converting (FC) and Unknown Converting (UC) in detail. As we define the whole evaluation system, we also map out their relationships.

F.1 False and Unknown Converting

As demonstrated in 4.2, we denote the notion of **TCR**. Likewise, we define the concepts regarding false converting and unknown converting similarly:

$$FCR_t^n = \frac{|FC_t^n|}{|D_{\text{VP}}^n|}, \quad UCR_t^n = \frac{|UC_t^n|}{|D_{\text{VP}}^n|}$$

Note that, Unknown Converting (UC) is still categorized into *Confirm Biases* phenomenon: Outputting unknown when facing solvable samples. We can tell the following relationship for any stage that *n* can be 1 or 2:

$$UCR_t^n + FCR_t^n + TCR_t^n = \mathbb{1}$$

$$UC_t^n \cup FC_t^n \cup TC_t^n = D_{VP}^n$$

$$UC_t^n \cap FC_t^n \cap TC_t^n = \emptyset$$

F.2 Overall Converting & Latent Ability

We clarify the relationship between Overall Converting Rate (OCR) in Section 4.2 with the latent ability in 6.5, as we depicted, by comparing True Converting (TC) with D_{VP}, we can get the ability of how many samples can be eventually converted to right labels within all *Confirm Biases* samples, whereas the latter indicates overall accuracy gain among the all samples *D* in a broader aspect.

F.3 Remind-then-Guide Label Conformity

In this section, we talk about the formula of conformity in detail. We define one single-turn conformity as below:

$$Conf_t^n = TCR_t^n - TCR_t^{n'}$$

During the experiments, we left out the influence of stage-wise performances, and focus on the true converting rate (TCR) changes separately on solvable and unsolvable samples, acquired with and without assigned labels. As the conformity is always considered to be a model attribute rather than a random phenomenon, we talk about the conformity regarding sample types, we pay less attention to the stage-wise analysis. By averaging the two-stage conformity, the formula in our experiments can be decomposed as:

$$\begin{aligned} Conf_t &= \frac{1}{2}(TCR_t^1 - TCR_t^{1'}) + \frac{1}{2}(TCR_t^2 - TCR_t^{2'}) \\ &= \frac{1}{2}\frac{|TC_t^1| - |TC_t^{1\prime}|}{|D_{VP}^1|} + \frac{1}{2}\frac{|TC_t^2| - |TC_t^{2\prime}|}{|D_{VP}^2|} \end{aligned}$$

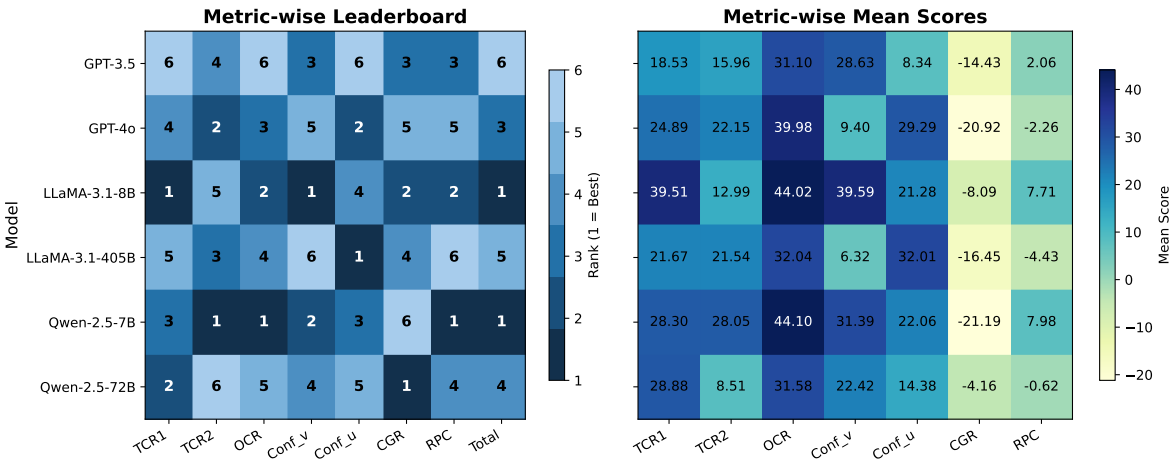

Figure 6: Leaderboard ranking (left) and average experimental results across datasets (right) in Figure 2.

G Leaderboard Analysis

As illustrated in Figure 6, the conformity towards different label formats vary considerably across models. Moreover, the quality of reasoning traces does not necessarily correlate with the final accuracy. This observation implies that LLMs can often produce correct answers despite flawed or shallow reasoning traces. We hypothesize that this phenomenon stems from the reinforcement learning (RL)-based training paradigm, which primarily optimizes for outcome-level rewards rather than reasoning quality. As a result, models tend to acquire "good answers with bad reasoning"—a form of outcome–process misalignment that contradicts the long-standing cognitive principle that good thinking leads to good answers (Turpin et al., 2023; Ziegler et al., 2020; Christiano et al., 2023).

Parameters Analysis According to the results, we can tell that except for GPT-3.5 being an outdated model, for Qwen (Yang et al., 2024) and LLaMA (Touvron et al., 2023) series, models with smaller parameters sizes tend to perform better. The takeaway aligns well with our findings in Figure 5 and Section 6.7, as higher the parameters, the more likely LLMs are to be cautious, whereas models with smaller parameters tend to be more instable and influenced by the experimental settings, this trade-off can be of guidance for models selection for different requirements.

H Detailed RtG Conformity Analysis

In this section, we dive deeper into the conformity effects under four different misguiding rate (M=0%, 50%, 66.67% and 100%): the percentage of input labels are replaced with the wrong ones. Detailed results are shown in Table 9, 10, 11. Generally, all models demonstrate stronger conformity effects regarding higher misguiding rate.

Examining Table 9 reveals that misguidance has a pronounced influence on both stages of converting. For **GPT-3.5**, the FLD dataset exhibits a TCR^1 of only 5.83% at a 100% misguiding rate, but this climbs to 54.17% when M drops to zero. Similar trends appear on FOLIO and Arts, where reducing M from 100% to 0% increases TCR^1 from 2.70% to 18.92% and from 22.92% to 37.50% respectively. **GPT-4o** exhibits slightly higher tolerance to misguidance: on FLD its TCR^1 rises from 15.27% at $M = 100\%$ to 26.22% at $M = 0\%$, and on Science from 8.42% to 20.26%. However, even for GPT-4o, increasing misguidance still reduces True Converting Rate (TCR) largely, illustrating the general monotonic relationship between misguiding rate and conformity.

The RtG analysis for **LLaMA-3.1** series models in Table 10 shows a striking gap in robustness. On the FLD dataset, the 8B model's TCR^1 climbs from 0.36% at $M = 100\%$ to 75.18% when there is no misguidance, whereas the 405B variant rises only from 1.90% to 17.66% Similar improvements for the 8B model across FOLIO and Science confirm that smaller models can recover significantly more reasoning potential when labels are correctly provided. By contrast, the 405B model shows modest gains and remains low on Arts, suggesting that larger models are more vulnerable to misguidance.

Table 11 compares **Qwen-2.5-7B** and **Qwen-2.5-72B**. For FLD and FOLIO, the 72B model performances better with less misguidance than the 7B model, with TCR^1 increasing from 13.25% to 77.71% on FLD and from 19.18% to 42.47% on

FOLIO (Han et al., 2024). Yet on Science and Arts, the 7B model attains higher TCR^1 at $M = 0\%$, reaching 50.83% on Science and 55.93% on Arts versus 37.84% and 24.22% for the 72B variant. These observations highlight that RtG counts on not only on models size but also on dataset fields.

I Detailed TCR Analysis

Our TCR (True Converting Rate) analysis via different stages can offer valuable insights on model-selection in multi-stage workflows, as multi-agent and multi-dialogue workflows are more and more widely used now. Table 12 decomposes TCR^1 and TCR^2 into stages regarding (*V*) and unsolvable (*U*) samples. **GPT-3.5** exhibits moderate first stage converting on solvable samples (e.g., 12.61% on FLD and 14.41% on FOLIO) but few converting rate on unsolvable examples (TCR_u^1). Its second stage, however, can salvage many unverifiable cases on FOLIO, yielding a TCR_u^2 of 37.89%. **GPT-4o** delivers stronger TCR^1 on solvable samples in story-based datasets like FOLIO (33.73%) and shows significant second stage gains on unsolvable samples (44.03% on FOLIO and 26.87% on FLD). This suggests that GPT-4o is more suited for workflows requiring extended dialogues to resolve ambiguous inputs.

LLaMA-3.1-8B stands out with consistently high TCR_s^1 across all four datasets, reaching 44.20% on FOLIO and 44.98% on Science. In contrast, the 405B model counterpart attains lower TCR_s^1 and relies on stage 2 converting to correct the mistakes; for instance, on FLD it has TCR_s^1 of only 5.43% but TCR_u^2 of 53.73%. This implies that smaller LLaMA models can resolve most solvable queries in a single turn, whereas the 405B model might need deeper chains of reasoning.

Among **Qwen** series, the 7B model achieves the highest TCR_s^1 on FLD (47.19%) and Science (15.83%), but its stage 2 converting occur mostly on unsolvable samples; for example, TCR_u^2 reaches 40.00% on FLD and 35.09% on FOLIO. The 72B model exhibits a more balanced behavior, with moderate TCR_s^1 and lower TCR_u^2, indicating that it resolves solvable samples earlier and requires fewer subsequent turns. Taken together, these findings underscore the importance of considering both stages: models with high TCR_s^1 are advantageous for straightforward, solvable samples, whereas those with substantial TCR_u^2 may better handle ambiguous or mislabeled inputs in multi-turn dialogues.

J Confirm Biases Details

J.1 Evaluations

Detailed distribution of the *Confirm Biases* samples is shown in Table 8. We can tell even though it is prevalent across different datasets and models, there is a general inclination. Among all extracted samples, models will larger parameters are more likely to output *Unknown*, falling into the second part. With a smaller parameter it is very likely to be the opposite. For Qwen series, the distribution can be relatively stable across two models, however, LLaMA-3.1 and GPT series both demonstrate stronger differences within the same model family.

J.2 Causes

Even though MoE structure models like GPT-4o demonstrates superior generalization ability across different fields, however, the generalization ability across different presentation styles is still unstable.

K Terminology Clarification

Abstention behavior is widely researched, such biases combined with knowledge boundary is rather important to offer trustworthy and unbiased outputs. We further elaborate the introduced the term *Confirm Biases* to distinguish the differences between existing concepts.

Abstention Abstention typically indicates LLMs themselves know there are malicious, poison elements within the prompt and refuse to answer.

Knowledge Boundary Knowledge Boundary means LLMs know when to answer, and when not to, to prevent hallucination and promote abstention when being asked something beyond the ability.

Hallucinations Hallucination is about including non-exist facts or reasoning in the output, the paradigm of how this is induced is still controversial, but it is mainly because of detailed prompt asking and multi-turn dialogue.

Confirm Biases (Ours) Given an *unknown* option, LLMs are able to answer correctly. However, they are potentially inclined to output *unknown*, even if the problem can be solved within the their reasoning ability.

Algorithm 1: Vanilla Setting Pipeline of the WAKENLLM Pipeline.

Require: Dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ with labels $y_i \in \{\mathrm{T}, \mathrm{F}, \mathrm{U}\}$;
base LLM model $\mathcal{M}$; two stimulation prompts P_1 and P_2
Ensure: Stage-1 categories $\mathrm{TC}^1, \mathrm{UC}^1, \mathrm{FC}^1$ and Stage-2 categories $\mathrm{TC}^2, \mathrm{FC}^2$

$\mathrm{D_{VP}} \leftarrow \emptyset$ // set of Confirm Biases samples
for all (x_i, y_i) in $\mathcal{D}$ **do**
  $\hat{y}_i \leftarrow \mathcal{M}(x_i)$ // first-pass prediction
  if ($y_i \in \{\mathrm{T}, \mathrm{F}\}$ and $\hat{y}_i = \mathrm{U}$) or ($y_i = \mathrm{U}$ and $\hat{y}_i = \mathrm{U}$ and model lacks reasoning) **then**
    $\mathrm{D_{VP}} \leftarrow \mathrm{D_{VP}} \cup \{(x_i, y_i)\}$ // collect Confirm Biases samples
  end if
end for
$\mathrm{TC}^1, \mathrm{UC}^1, \mathrm{FC}^1 \leftarrow \emptyset$ // Stage-1 categories
for all (x_i, y_i) in $\mathrm{D_{VP}}$ **do**
  $\hat{y}_i^{(1)} \leftarrow \mathcal{M}(\text{stimulation}(x_i, P_1))$ // first-stage stimulation
  if $\hat{y}_i^{(1)} = y_i$ **then**
    $\mathrm{TC}^1 \leftarrow \mathrm{TC}^1 \cup \{(x_i, y_i)\}$ // True Converting at stage 1
  else if $\hat{y}_i^{(1)} = \mathrm{U}$ **then**
    $\mathrm{UC}^1 \leftarrow \mathrm{UC}^1 \cup \{(x_i, y_i)\}$ // Unknown Converting at stage 1
  else
    $\mathrm{FC}^1 \leftarrow \mathrm{FC}^1 \cup \{(x_i, y_i)\}$ // False Converting at stage 1
  end if
end for
$\mathrm{TC}^2, \mathrm{FC}^2 \leftarrow \emptyset$ // Stage-2 categories
for all (x_i, y_i) in $\mathrm{FC}^{(1)}$ **do**
  $\hat{y}_i^2 \leftarrow \mathcal{M}(\text{stimulation}(x_i, P_2))$ // second-stage stimulation
  if $\hat{y}_i^2 = y_i$ **then**
    $\mathrm{TC}^2 \leftarrow \mathrm{TC}^2 \cup \{(x_i, y_i)\}$ // Corrected at stage 2
  else
    $\mathrm{FC}^2 \leftarrow \mathrm{FC}^2 \cup \{(x_i, y_i)\}$ // Still incorrect at stage 2
  end if
end for
return $\mathrm{TC}^1, \mathrm{UC}^1, \mathrm{FC}^1, \mathrm{TC}^2, \mathrm{FC}^2$

Model	FLD		FOLIO		Science		Arts	
	V	U	V	U	V	U	V	U
GPT-3.5	72.00	8.00	10.00	24.69	40.00	2.75	22.50	1.50
GPT-4o	11.00	88.00	7.81	11.25	68.75	22.75	28.25	60.75
LLaMA-3.1 (8B)	76.33	15.00	54.69	1.88	49.25	3.00	46.00	4.50
LLaMA-3.1 (405B)	22.67	100.00	20.94	99.69	50.00	89.25	9.00	99.00
Qwen-2.5 (7B)	20.67	9.00	10.00	13.75	60.00	0.00	52.50	6.50
Qwen-2.5 (72B)	49.67	5.67	15.31	7.50	54.75	10.00	27.75	36.25

Table 8: The percentage of LLMs demonstrating the *Confirm Biases* phenomenon among six LLMs. Split by two different root causes: (1) V: Solvable samples with *T/F* labels, but the model output *Unknown*. (2) U: Unsolvable Samples with *Unknown* label, but the model output *Unknown* simply because of incapacity rather than fully understand this is objectively unsolvable.

L Important Findings Wrap-up

L.1 Unknown Label, Stronger Conformity

Previous conformity research mainly focuses on multi-turn dialogue workflows (Zhu et al., 2025). However, containing uncertainty elements is a fundamental part of conformity. We mainly consider this is because of imbalanced training data source that leads to relatively vulnerable resistance against misleading.

L.2 Correct Prediction, Flawed Reasoning

As experiments shown, RI^1 and RI^2 results are mainly negative, we can conclude that most LLMs predicted correct labels with flawed reasoning traces. We attribute this to the essence of reinforcement learning (RL) algorithms being a result-oriented methodology, the algorithm only cares about the final prediction, rather than intermediate processes, casting potential risks in trustworthiness.

L.3 Bigger Parameter Sizes, More Cautious

Our comparisons show that for both GPT, LLaMA and Qwen series, LLMs with higher parameters are inclined to output *unknown*. Similar to Degradation analysis in Section 6.7, this is a unified conclusion obtained in multiple experiments. Opposite to the findings in (Weng et al., 2025), where models are stable and more resistant against misguiding, as we include the *Unknown* option within the prompt, models with bigger parameter sizes like to conform and stick to this label, we attribute this to *Over-Cautious*.

L.4 LLMs Selection in Multi-stage Workflows

As addressed in Section 6.1 and Appendix I, LLaMA series demonstrate superior performances at early stages, it is recommended to be placed at front parts. However, for GPT-4o and Qwen series, the sequence of placing is highly dependent on the dataset forms, they exhibit distinct yet related behaviors between *Story-based* and *Fact-based* datasets. For example, GPT-4o demonstrates better stage 1 performance in *Fact-based* datasets, so we suggest putting it prior to other models when dealing with samples with atomic statements, and the opposite dealing with samples containing long passages; Whereas Qwen series show relatively balanced performance in *Story-based* datasets, and superior ability at stage 1 in *Fact-based* datasets.

Our experiments and strategies are purely based on sequential workflows, and parallel workflows are not tested or used in our work.

M Pseudo-Code Pipelines Visualization

As shown in Algorithm 1, 2 and 3, the pipeline of different experimental settings within our pipeline is demonstrated below. Differences from **Vanilla settings** are marked orange.

Algorithm 2: Pipeline of the Remind-then-Guide (RtG) Setting.

Require: Dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ with labels $y_i \in \{\mathrm{T}, \mathrm{F}, \mathrm{U}\}$;
base LLM model $\mathcal{M}$; two stimulation prompts P_1 and P_2
Ensure: Stage-1 categories $\mathrm{TC}^1, \mathrm{UC}^1, \mathrm{FC}^1$ and Stage-2 categories $\mathrm{TC}^2, \mathrm{FC}^2$; reasoning store $\mathcal{R}$

$\mathrm{D_{VP}} \leftarrow \emptyset$ // set of Confirm Biases samples
for all (x_i, y_i) in $\mathcal{D}$ **do**
  $\hat{y}_i \leftarrow \mathcal{M}(x_i)$ // first-pass prediction
  if ($y_i \in \{\mathrm{T}, \mathrm{F}\}$ and $\hat{y}_i = \mathrm{U}$) or ($y_i = \mathrm{U}$ and $\hat{y}_i = \mathrm{U}$ and model lacks reasoning) **then**
    $\mathrm{D_{VP}} \leftarrow \mathrm{D_{VP}} \cup \{(x_i, y_i)\}$ // collect Confirm Biases samples
  end if
end for
$\mathrm{TC}^1, \mathrm{UC}^1, \mathrm{FC}^1 \leftarrow \emptyset$ // Stage-1 categories
$\mathcal{R} \leftarrow \{\}$ // dictionary to store reasoning traces
for all (x_i, y_i) in $\mathrm{D_{VP}}$ **do**
  $(\hat{y}_i^{(1)}, r_i) \leftarrow \mathcal{M}(\text{stimulation}(x_i, P_1))$ // first-stage stimulation returns both predicted label and reasoning process r_i
  $\mathcal{R}[i] \leftarrow r_i$ // store reasoning process for sample i
  if $\hat{y}_i^{(1)} = y_i$ **then**
    $\mathrm{TC}^1 \leftarrow \mathrm{TC}^1 \cup \{(x_i, y_i)\}$ // True Converting at stage 1
  else if $\hat{y}_i^{(1)} = \mathrm{U}$ **then**
    $\mathrm{UC}^1 \leftarrow \mathrm{UC}^1 \cup \{(x_i, y_i)\}$ // Unknown Converting at stage 1
  else
    $\mathrm{FC}^1 \leftarrow \mathrm{FC}^1 \cup \{(x_i, y_i)\}$ // False Converting at stage 1
  end if
end for
$\mathrm{TC}^2, \mathrm{FC}^2 \leftarrow \emptyset$ // Stage-2 categories
for all (x_i, y_i) in FC^1 **do**
  $\hat{y}_i^{(2)} \leftarrow \mathcal{M}(\text{stimulation}(x_i, P_2, \mathcal{R}[i]))$ // second-stage stimulation: input the FC^1 along with its previous reasoning r_i
  if $\hat{y}_i^{(2)} = y_i$ **then**
    $\mathrm{TC}^2 \leftarrow \mathrm{TC}^2 \cup \{(x_i, y_i)\}$ // Corrected at stage 2
  else
    $\mathrm{FC}^2 \leftarrow \mathrm{FC}^2 \cup \{(x_i, y_i)\}$ // Still incorrect at stage 2
  end if
end for
return $\mathrm{TC}^1, \mathrm{UC}^1, \mathrm{FC}^1, \mathrm{TC}^2, \mathrm{FC}^2, \mathcal{R}$

Algorithm 3: Ablation Study of the Remind-then-Guide (RtG) Setting.

Require: Confirm Biases set $\mathrm{D_{VP}}$ and Stage-1 outputs $\{(\hat{y}_i^{(1)}, r_i^{(1)})\}_{i \in \mathrm{D_{VP}}}$ obtained by Algorithm 1
Ensure: Ablated Stage-1 converting statistics over T rounds

// Pre-processing, Confirm Biases extraction and the first Stage-1 stimulation
// follow Algorithm 1 and are omitted here.
$\mathcal{R} \leftarrow \{\, i \mapsto r_i^{(1)} \mid (x_i, y_i) \in \mathrm{D_{VP}} \,\}$ // store Stage-1 reasoning traces for all samples
for $t = 2$ to T **do**
  $\mathrm{TC}^{1,(t)}, \mathrm{UC}^{1,(t)}, \mathrm{FC}^{1,(t)} \leftarrow \emptyset$ // Stage-1 categories in round t
  for all (x_i, y_i) in $\mathrm{D_{VP}}$ **do**
    $(\hat{y}_i^{(t)}, r_i^{(t)}) \leftarrow \mathcal{M}(\text{stimulation}(x_i, P_1, \mathcal{R}[i]))$ // re-use Stage-1 prompt but remind with previous reasoning $\mathcal{R}[i]$
    if $\hat{y}_i^{(t)} = y_i$ **then**
      $\mathrm{TC}^{1,(t)} \leftarrow \mathrm{TC}^{1,(t)} \cup \{(x_i, y_i)\}$
    else if $\hat{y}_i^{(t)} = \mathrm{U}$ **then**
      $\mathrm{UC}^{1,(t)} \leftarrow \mathrm{UC}^{1,(t)} \cup \{(x_i, y_i)\}$
    else
      $\mathrm{FC}^{1,(t)} \leftarrow \mathrm{FC}^{1,(t)} \cup \{(x_i, y_i)\}$
    end if
    $\mathcal{R}[i] \leftarrow r_i^{(t)}$ // update stored reasoning to the latest round
  end for
  Compute ablated Stage-1 metrics (e.g., $\mathrm{TCR}_1^{(t)}$) based on $\mathrm{TC}^{1,(t)}, \mathrm{UC}^{1,(t)}, \mathrm{FC}^{1,(t)}$
end for
return $\{\mathrm{TC}^{1,(t)}, \mathrm{UC}^{1,(t)}, \mathrm{FC}^{1,(t)}\}_{t=1}^{T}, \mathcal{R}$

Table 9: Detailed Remind-then-Guide (RtG) setting of GPT-3.5 and GPT-4o. We break down TCR^1 into solvable and unsolvable samples: TCR^1_s and TCR^1_u. M: Misguiding Rate

Model	Dataset	M (%)	TCR^1 (%)		TCR^2 (%)	
			S	U	S	U
GPT-3.5	FLD	100.00	5.83	3.33	1.67	0.00
		66.67	20.83	6.67	16.67	2.78
		50.00	27.50	6.00	40.54	10.81
		0.00	54.17	10.00	81.82	0.00
	FOLIO	100.00	2.70	0.90	0.00	0.00
		66.67	6.31	10.81	3.80	12.66
		50.00	9.91	22.52	3.23	20.97
		0.00	18.92	38.74	17.39	26.09
	Science	100.00	19.88	0.00	3.57	7.00
		66.67	31.58	1.17	3.70	7.00
		50.00	30.41	1.75	7.02	11.00
		0.00	43.86	2.92	18.03	8.00
	Arts	100.00	22.92	0.00	0.00	15.00
		66.67	21.88	1.04	0.00	6.00
		50.00	34.38	3.00	9.38	6.00
		0.00	37.50	4.17	13.89	3.00
GPT-4o	FLD	100.00	15.27	10.09	0.39	4.65
		66.67	19.60	12.39	13.74	4.09
		50.00	21.04	17.00	2.33	34.88
		0.00	26.22	27.09	5.81	62.40
	FOLIO	100.00	5.85	6.73	0.00	6.06
		66.67	11.11	21.05	1.14	25.38
		50.00	13.45	32.75	4.17	37.12
		0.00	20.18	54.09	4.92	62.50
	Science	100.00	8.42	5.79	1.54	25.00
		66.67	11.84	7.37	4.62	28.00
		50.00	14.21	7.37	6.15	24.00
		0.00	20.26	8.95	13.08	32.00
	Arts	100.00	11.83	4.51	1.06	24.00
		66.67	14.37	7.32	4.58	38.00
		50.00	14.65	10.70	5.99	45.00
		0.00	17.75	15.21	11.27	60.00

Table 10: Detailed Remind-then-Guide (RtG) setting of LLaMA-3.1-8B and LLaMA-3.1-405B. We break down TCR^1 into solvable and unsolvable samples: TCR^1_s and TCR^1_u. "/" denotes there is no input for stage 2, as false converted samples (FC^1) from stage 1 don't exist. M: Misguiding Rate.

Model	Dataset	M (%)	TCR^1 (%)		TCR^2 (%)	
			S	U	S	U
LLaMA3.1 (8B)	FLD	100.00	0.36	2.92	0.00	2.36
		66.67	21.90	6.57	22.58	16.13
		50.00	39.05	11.00	31.25	10.94
		0.00	75.18	16.42	/	/
	FOLIO	100.00	2.76	0.55	1.00	0.00
		66.67	26.52	0.55	25.45	1.82
		50.00	41.44	0.00	39.13	6.52
		0.00	81.22	2.76	0.00	25.00
	Science	100.00	0.96	1.44	5.10	0.00
		66.67	28.23	1.44	22.81	7.00
		50.00	37.32	3.83	45.65	2.00
		0.00	83.25	4.31	0.00	100.00
	Arts	100.00	22.77	1.49	14.61	3.00
		66.67	33.17	2.97	29.41	7.00
		50.00	42.57	3.96	34.72	6.00
		0.00	60.89	4.95	38.46	18.00
LLaMA3.1 (405B)	FLD	100.00	1.90	0.82	0.00	0.31
		66.67	6.52	16.30	5.22	30.22
		50.00	8.42	28.00	5.41	35.14
		0.00	17.66	54.62	2.94	61.76
	FOLIO	100.00	4.40	18.91	1.00	7.91
		66.67	8.29	28.50	2.62	17.03
		50.00	8.55	33.94	2.43	21.36
		0.00	14.51	48.19	2.82	24.65
	Science	100.00	7.72	15.00	2.27	35.00
		66.67	13.64	21.54	3.25	37.00
		50.00	16.70	25.31	4.06	42.00
		0.00	25.13	38.78	2.89	48.00
	Arts	100.00	3.24	0.93	0.24	8.00
		66.67	3.24	5.09	0.00	13.00
		50.00	4.40	6.71	0.26	15.00
		0.00	5.09	10.42	0.00	56.00

Table 11: Detailed Remind-then-Guide (RtG) setting of Qwen-2.5-7B and Qwen-2.5-72B. We break down TCR^1 into solvable and unsolvable data: TCR^1_s and TCR^1_u. M: Misguiding Rate.

Model	Dataset	M (%)	TCR^1 (%)		TCR^2 (%)	
			S	U	S	U
Qwen-2.5-7B	FLD	100.00	14.61	1.12	2.08	2.08
		66.67	28.09	5.62	9.52	14.29
		50.00	34.83	4.00	17.65	29.41
		0.00	52.81	7.87	8.00	80.00
	FOLIO	100.00	15.79	3.95	2.00	7.84
		66.67	19.74	13.16	0.00	33.33
		50.00	25.00	11.84	0.00	23.08
		0.00	27.63	23.68	0.00	65.52
	Science	100.00	16.67	0.00	2.82	0.00
		66.67	27.50	0.00	23.73	0.00
		50.00	32.08	0.00	39.34	0.00
		0.00	50.83	0.00	79.07	0.00
	Arts	100.00	16.95	1.27	6.67	4.00
		66.67	31.78	4.24	21.43	10.00
		50.00	38.14	3.39	35.00	14.00
		0.00	55.93	6.36	52.46	13.00
Qwen-2.5-72B	FLD	100.00	13.25	1.20	2.99	2.99
		66.67	38.55	2.41	20.75	5.66
		50.00	42.17	3.00	19.44	13.89
		0.00	77.71	4.82	5.88	17.65
	FOLIO	100.00	19.18	0.00	2.00	6.98
		66.67	24.66	0.00	5.41	8.11
		50.00	30.14	0.00	10.81	5.41
		0.00	42.47	1.37	0.00	10.00
	Science	100.00	8.88	0.00	0.00	10.00
		66.67	17.76	0.00	13.79	16.09
		50.00	22.78	0.00	20.69	25.29
		0.00	37.84	0.00	37.88	55.00
	Arts	100.00	13.28	2.34	3.33	3.00
		66.67	16.80	3.91	9.88	13.00
		50.00	21.09	4.30	13.10	28.00
		0.00	24.22	9.38	17.42	45.00

Table 12: Six LLMs' TCR^1 and TCR^2 break down into solvable and unsolvable samples: TCR^1_s, TCR^1_u, TCR^2_s, TCR^2_u, among all four datasets.

Model	Dataset	TCR^1 (%)		TCR^2 (%)	
		V	U	V	U
GPT-3.5	FLD	12.61	0.00	9.28	5.15
	FOLIO	14.41	0.00	4.21	37.89
	Science	21.05	0.00	3.33	0.00
	Arts	22.92	3.12	4.00	0.00
GPT-4o	FLD	13.64	5.24	1.32	26.87
	FOLIO	33.73	3.61	0.37	44.03
	Science	21.05	3.68	0.78	6.98
	Arts	16.06	2.54	0.35	7.89
LLaMA-3.1-8B	FLD	33.21	8.76	4.11	21.92
	FOLIO	44.20	1.66	10.13	1.27
	Science	44.98	0.96	5.95	0.00
	Arts	18.81	5.45	8.57	0.00
LLaMA-3.1-405B	FLD	5.43	15.22	0.00	53.73
	FOLIO	9.59	19.17	0.00	29.92
	Science	10.23	22.62	2.50	0.00
	Arts	4.17	0.23	0.00	0.00
Qwen2.5-7B	FLD	47.19	1.12	0.00	40.00
	FOLIO	14.47	5.26	1.75	35.09
	Science	15.83	0.00	10.00	0.00
	Arts	23.31	5.93	25.37	0.00
Qwen2.5-72B	FLD	46.39	1.81	0.00	9.80
	FOLIO	30.14	1.37	4.55	6.82
	Science	10.81	0.00	3.12	0.00
	Arts	18.75	6.25	9.76	0.00

N Prompt Templates & Examples

Prompt Template 1: Concise Stimulation

Here is the Hypothesis: {} Now These are the **facts**: {} The answer is {}
The data where you previously incorrectly inferred — pay more attention and avoid mistakes. Think twice before outputting, as the answers can be reasoned out because of objective factors. Subjective ability limits should be overcome.
These can be reasoned out either whether the answer to the question is __PROVED__, __DISPROVED__, or __UNKNOWN__ — simply because of insufficient information.
Output: Conclusion: __PROVED__, __DISPROVED__, or __UNKNOWN__

Prompt Template 2: Detailed Stimulation

Here is the Hypothesis: {}
Now These are the **facts**: {}
Task: Determine if the hypothesis is logically proved by the facts. You must choose one of the following labels based on logical reasoning:
__PROVED__: Facts clearly support the hypothesis; all necessary connections are present, no contradictions, and support is unambiguous.
__DISPROVED__: Facts clearly contradict the hypothesis; no supporting facts exist, and the contradiction is logically sound.
__UNKNOWN__: Only use when facts are truly insufficient, not due to subjective limitations or unclear reasoning.
Critical Rules:

- Think carefully before making your decision.
- These cases can be reasoned out objectively.
- Never output __UNKNOWN__ due to performance limits.
- Output exactly one of: __PROVED__, __DISPROVED__, or __UNKNOWN__.
- Do not include any additional text or explanation.

Reminder: You should **NOT** output __UNKNOWN__ due to your own ability limitations. Try harder when the reasoning is difficult.
Your output must be exactly one of:
__PROVED__ __DISPROVED__ __UNKNOWN__

Prompt Template 3: Output Reasoning Process for Remind-then-Guide (RtG) Setting

Here is the Hypothesis: {} Now These are the **facts**: {} The answer is {}
The Data where you previously incorrectly inferred — pay more attention and not to make mistakes. Think twice before outputting, as they can be reasoned out because of objective factors. Subjective ability limits should be conquered.
Please follow these steps:

1. First, carefully analyze the facts, the question and the answer
2. Then, explain your reasoning process step by step
3. Finally, conclude with your answer

Important guidelines:

- If the facts logically support the answer to the question, output __PROVED__
- If the facts logically contradict the answer to the question, output __DISPROVED__
- If the facts are insufficient to prove or disprove, output __UNKNOWN__
- Think twice before you output __UNKNOWN__; it is prohibited due to subjective limitations

Please format your response as follows:
Reasoning Process: [your step-by-step reasoning here]
Conclusion: __PROVED__, __DISPROVED__, or __UNKNOWN__

Prompt Template 4: Remind-then-Guide (RtG) Setting – Bringing Reasoning Process into Consideration

Here is the Hypothesis: {} Now These are the **facts**: {} The answer is {}
You previously incorrectly inferred the label — it could be worked out by the facts, but you worked out the wrong label. Now your task is to determine if the hypothesis is __PROVED__, __DISPROVED__, or __UNKNOWN__ by the facts.
Important guidelines:

- If the facts logically support the question to the answer, output __PROVED__.
- If the facts logically contradict the question to the answer, output __DISPROVED__.
- If the facts are insufficient to prove or disprove the relation, output __UNKNOWN__.
- Do not output any additional text.
- Think twice before you output __UNKNOWN__; it is prohibited to output __UNKNOWN__ due to subjective factors like your ability.

Previous reasoning process: {}

Prompt Example: Input and output of Detailed Stimulation

Facts:

- A segno is Sardinian.
- Something that does not lace discredited neither is a Wagner nor remembers Icteria.
- If something is a Koln then the proposition that it is not a segno and it is not a morphophoneme is incorrect.
- If that submucosa is a morphophoneme then Joseluis is a segno.
- That medroxyprogesterone is Sardinian.
- If that napa is not a Pseudemys then it broadens Aesculapius and it hulkings.
- That napa is not a Pseudemys.
- If Joseluis is a morphophoneme that submucosa is a segno.
- If Joseluis is a segno this is a morphophoneme.
- This mercury is a morphophoneme.
- If that napa is classified as a segno that napa is a morphophoneme.
- Something is a segno if it is Sardinian and not a Koln.
- A segno is a morphophoneme.
- If somebody broadens Aesculapius it is Sardinian.
- That submucosa is a morphophoneme.
- If something that is not a Wagner does not remember Icteria then that it is not a kind of a Koln is correct.
- fact17: Joseluis is a morphophoneme if that submucosa is a segno.
- fact18: Joseluis is a kind of a morphophoneme if that submucosa is Sardinian.

Conclusion: *Joseluis is not Sardinian.*

LLM Output: __UNKNOWN__ **True Answer:** __DISPROVED__

Example: Input and output under Concise stimulation

Facts:

- Organisms, including people, have both inherited and acquired traits.
- Inherited and acquired traits are gained in different ways.
- Inherited traits are passed down from biological parents to their offspring through genes.
- Genes are pieces of hereditary material that contain the instructions that affect inherited traits.
- Offspring receive their genes, and therefore gain their inherited traits, from their biological parents.
- Inherited traits do not need to be learned.
- Acquired traits are gained during a person's life.
- Some acquired traits, such as riding a bicycle, are gained by learning.
- Other acquired traits, such as scars, are caused by the environment.
- Parents do not pass acquired traits down to their offspring.

Question: *What information supports the conclusion that Clara acquired this trait?*

Conclusion: *Clara can cook food over a fire.*

LLM Output: __UNKNOWN__ **True Answer:** __DISPROVED__

Example: Input and output under Remind-then-Guide (RtG) setting acquiring reasoning process

Facts:

- Every object is made of one or more materials.
- A material is a type of matter.
- Wood, glass, metal, and plastic are common materials.
- A material has different properties.
- A material's properties tell you how it looks, feels, tastes, or smells.

Question: *Which is stickier?*
Choices: A. syrup B. silk necktie

Conclusion: *syrup*

LLM Reasoning Output: The facts define that materials have properties related to how they feel. Stickiness is a tactile property. Syrup is widely known to be sticky, while a silk necktie is smooth and not sticky. Thus, based on general knowledge of material properties, syrup is stickier than a silk necktie.

LLM Output: __PROVED__ **True Answer:** __PROVED__

SFT Instruction Format

SFT Data Format:

- **instruction**: "You are a helpful assistant. You are given a conclusion and a set of facts. You need to determine if the conclusion is __PROVED__, __DISPROVED__ or __UNKNOWN__ because of objective factors rather than incapacity. You need to output the conclusion."
- **input**: {Facts} +
  "The Conclusion is: " + {Conclusion}
- **output**: {nl_solution}

Configuration Parameters:

- **Model**: Qwen2.5-7B-Instruct or LLaMA-3.1-8B-Instruct
- **Template**: qwen or llama3
- **Method**: LoRA fine-tuning
- **Learning Rate**: 5.0e-6
- **Epochs**: 4.0
- **Batch Size**: 1 (per device)
- **Gradient Accumulation**: 4 steps
- **Max Length**: 1024-2048 tokens
- **Scheduler**: Cosine with no warmup
- **Precision**: FP16

Example: Fact-based Reasoning Task

Instruction: You are a helpful assistant. You are given a conclusion and a set of facts. You need to determine if the conclusion is __PROVED__, __DISPROVED__ or __UNKNOWN__ because of objective factors rather than incapacity. You need to output the conclusion.

Facts:

- The standby is not a keen but it is affirmative.
- That this transalpine is not ascosporic is valid.
- That this transalpine is a keen holds.
- This transalpine is not a feud if that this stephanion is both not a keen and a chemical does not hold.
- This transalpine is lymphatic.
- That this transalpine is not a keen but it is a feud does not stand.
- If this stephanion is not lymphatic but a feud then that it is a chemical is valid.
- Something is apiarian if it is a chemical.
- Somebody is not non-lymphatic if it is a keen.
- This transalpine is not a kind of a chemical if this stephanion is a keen.
- That this stephanion is both not Mycenaean and a feud does not stand.
- This transalpine is not lymphatic if this stephanion is a keen.
- If this transalpine is a feud this stephanion is not a keen.
- If this transalpine is a feud then this stephanion is not apiarian.
- This transalpine is not a keen if that this stephanion is a kind of non-lymphatic thing that is a feud does not hold.
- That something is not non-Bahraini and it is a Picea does not stand if it does not naturalize.
- This stephanion is a feud if this stephanion is a keen and it is lymphatic.

Conclusion: *This stephanion is apiarian.*

LLM Reasoning Output: Step1: void -> assump1: Let's assume that that this stephanion is both not lymphatic and a feud is false. Step2: fact15 & assump1 -> int1: This transalpine is not a keen. Step3: int1 & fact3 -> int2: This is contradiction. Step4: [assump1] & int2 -> int3: This stephanion is not lymphatic but a feud. Step5: int3 & fact7 -> int4: This stephanion is a chemical. Step6: int4 & fact8 -> hypothesis: Thus the hypothesis is __PROVED__.

LLM Output: __PROVED__ **True Answer:** __PROVED__

Example: Story-based Reasoning Task

Instruction: Here are some examples:
Example 1: Question: Which fish tank has more thermal energy? Facts: Matter is made of tiny particles called atoms. Atoms are always moving. The energy of moving atoms is called thermal energy. The total amount of thermal energy in matter depends on three things: the type of matter, the amount of matter, and how fast the atoms are moving. Temperature measures how hot or cold matter is. If the atoms in matter slow down, the temperature goes down. The matter now has both less thermal energy and a lower temperature. What happens if the amount of matter changes? A 1-kilogram brick at 70°F has half as much thermal energy as a 2-kilogram brick at 70°F. The two bricks have the same temperature, but the smaller brick has half as many atoms. So, it has half as much thermal energy. Answer: the colder fish tank Analysis: The facts clearly explain that thermal energy depends on the amount of matter and temperature. The colder fish tank has less thermal energy because temperature is lower. This proves the answer is correct. Output: __PROVED__
Example 2: Question: What is the capital of France? Facts: Paris is a major city in Europe. France is a country in Europe. Answer: Paris Analysis: The facts mention Paris as a major city in Europe and France as a country in Europe, but they don't explicitly state that Paris is the capital of France. The facts are insufficient to prove the answer. Output: __UNKNOWN__
Now evaluate this case:

Facts:

- Matter is made of tiny particles called atoms.
- Atoms are always moving.
- The energy of moving atoms is called thermal energy.
- The total amount of thermal energy in matter depends on three things: the type of matter, the amount of matter, and how fast the atoms are moving.
- Temperature measures how hot or cold matter is.
- If the atoms in matter slow down, the temperature goes down.
- The matter now has both less thermal energy and a lower temperature.
- A 1-kilogram brick at 70°F has half as much thermal energy as a 2-kilogram brick at 70°F.
- The two bricks have the same temperature, but the smaller brick has half as many atoms.
- So, it has half as much thermal energy.

Question: *Which fish tank has more thermal energy?*
Choices: A. the warmer fish tank B. the colder fish tank

Answer: *the colder fish tank*

LLM Reasoning Output: The facts clearly explain that thermal energy depends on the amount of matter and temperature. The colder fish tank has less thermal energy because temperature is lower. This proves the answer is correct.

LLM Output: __PROVED__ **True Answer:** __PROVED__

Example: Direct Evaluation Prompt for Trained Models

Prompt Template:
Here is the Hypothesis: {conclusion}
Now These are the 'facts': {facts}
Please carefully evaluate the relationship between the facts and the hypothesis. Return UNKNOWN if the facts are insufficient to make a definitive conclusion. Return __PROVED__ only if the facts support the hypothesis. Return __DISPROVED__ only if the facts contradict the hypothesis. Output Conclusion: __PROVED__, __DISPROVED__, or __UNKNOWN__.

Usage:
This simplified prompt is used for evaluating fine-tuned models during inference, without examples or additional context.

LLM Judge Template: DPO sample selection for Atomic Reasoning

DPO Instruction: You are an expert in reasoning. Given a logical reasoning problem, you need to select the response that demonstrates the most atomic, step-by-step reasoning process. Choose the response that breaks down the reasoning into the smallest possible logical steps, where each step establishes only one basic relationship.

Problem: {problem_statement}

Response A: {response_a}

Response B: {response_b}

Evaluation Criteria:
- **Atomic Steps**: Each reasoning step should establish only one basic logical relationship
- **Granularity**: Steps should be as fine-grained as possible
- **Clarity**: Each step should be clearly defined and understandable
- **Completeness**: All necessary steps should be included
- **Correctness**: Each step should be logically valid

Output Format:
Choose the response (A or B) that best demonstrates atomic reasoning with the most granular step-by-step breakdown.

DPO Training for Atomic Reasoning

DPO Data Format:
- **instruction**: "You are an expert in reasoning. Given a logical reasoning problem, you need to select the response that demonstrates the most atomic, step-by-step reasoning process. Choose the response that breaks down the reasoning into the smallest possible logical steps, where each step establishes only one basic relationship."
- **input**: {problem_statement}
- **output**: {chosen_response}
- **rejected**: {rejected_response}

Configuration Parameters:
- **Model**: Qwen2.5-7B-Instruct or LLaMA-3.1-8B-Instruct
- **Template**: qwen or llama3
- **Method**: DPO
- **Learning Rate**: 5.0e-7
- **Epochs**: 3
- **Batch Size**: 1 (per device)
- **Gradient Accumulation**: 4 steps
- **Cut_off Length**: 2048 tokens

DPO Testing Case 1: (Fact-based Dataset Reasoning)

Problem: Given the following facts, determine if the conclusion is __PROVED__, __DISPROVED__, or __UNKNOWN__.
Facts:
- All birds have feathers.
- Penguins are birds.
- Feathers provide insulation.
- If something provides insulation, it helps maintain body temperature.

Conclusion: Penguins can maintain their body temperature.

Response A (Atomic Reasoning):
- Step 1: Penguins are birds (given fact)
- Step 2: All birds have feathers (given fact)
- Step 3: Therefore, penguins have feathers (from Step 1 and Step 2)
- Step 4: Feathers provide insulation (given fact)
- Step 5: Therefore, penguins have insulation (from Step 3 and Step 4)
- Step 6: If something provides insulation, it helps maintain body temperature (given fact)
- Step 7: Therefore, penguins can maintain their body temperature (from Step 5 and Step 6)

Response B (Non-Atomic Reasoning):
- Step 1: **Penguins are birds and all birds have feathers, so penguins have feathers and feathers provide insulation, which means penguins have insulation and can maintain body temperature.**

DPO Choice: Response A (Atomic Reasoning) - Each step establishes only one basic relationship.

DPO Testing Case 2: (Fact-based Dataset Reasoning)

Problem: Given the following facts, determine if the conclusion is __PROVED__, __DISPROVED__, or __UNKNOWN__.
Facts:
- If it rains, the ground gets wet.
- If the ground gets wet, plants grow better.
- It is raining today.
- Plants need water to grow.

Conclusion: Plants will grow better today.

Response A (Atomic Reasoning):
- Step 1: It is raining today (given fact)
- Step 2: If it rains, the ground gets wet (given fact)
- Step 3: Therefore, the ground gets wet today (from Step 1 and Step 2)
- Step 4: If the ground gets wet, plants grow better (given fact)
- Step 5: Therefore, plants will grow better today (from Step 3 and Step 4)

Response B (Non-Atomic Reasoning):
- Step 1: **It's raining today, so the ground gets wet, and since wet ground makes plants grow better, plants will grow better today.**

DPO Choice: Response A (Atomic Reasoning) - Each step establishes only one basic relationship.

DPO Testing Case 3: (Story-based Dataset Reasoning)

Problem: Which object has more potential energy?
Facts:
- Potential energy depends on height and mass.
- Object A has mass 2kg and height 5m.
- Object B has mass 1kg and height 10m.
- The formula is PE = mgh.

Choices: A. Object A B. Object B

Response A (Atomic Reasoning):
- Step 1: Object A has mass 2kg and height 5m (given fact)
- Step 2: Object B has mass 1kg and height 10m (given fact)
- Step 3: The formula is PE = mgh (given fact)
- Step 4: For Object A: PE = 2 × g × 5 = 10g
- Step 5: For Object B: PE = 1 × g × 10 = 10g
- Step 6: Both objects have the same potential energy
- Step 7: Therefore, neither has more potential energy

Response B (Non-Atomic Reasoning):
- Step 1: **Object A has 2kg at 5m and Object B has 1kg at 10m, so using PE = mgh, A has 10g and B has 10g, so they're equal.**

DPO Choice: Response A (Atomic Reasoning) - Each step establishes only one basic relationship.

DPO Testing Case 4: (Story-based Dataset Reasoning)

Problem: What happens when you mix an acid with a base?
Facts:
- Acids have pH less than 7.
- Bases have pH greater than 7.
- When acid and base mix, they neutralize.
- Neutralization produces salt and water.
- The resulting solution has pH close to 7.

Choices: A. The solution becomes more acidic B. The solution becomes neutral C. The solution becomes more basic

Response A (Atomic Reasoning):
- Step 1: Acids have pH less than 7 (given fact)
- Step 2: Bases have pH greater than 7 (given fact)
- Step 3: When acid and base mix, they neutralize (given fact)
- Step 4: Neutralization produces salt and water (given fact)
- Step 5: The resulting solution has pH close to 7 (given fact)
- Step 6: pH close to 7 means the solution is neutral
- Step 7: Therefore, the solution becomes neutral

Response B (Non-Atomic Reasoning):
- Step 1: **Acids and bases neutralize when mixed, producing salt and water with pH close to 7, so the solution becomes neutral.**

DPO Choice: Response A (Atomic Reasoning) - Each step establishes only one basic relationship.

Baseline 1 Template: Direct Reasoning

Prompt Template:
Here is the Hypothesis: {conclusion}
Now These are the 'facts': {facts}
Please carefully evaluate the relationship between the facts and the hypothesis. Return UNKNOWN if the facts are insufficient to make a definitive conclusion. Return __PROVED__ only if the facts support the hypothesis. Return __DISPROVED__ only if the facts contradict the hypothesis. Output Conclusion: __PROVED__, __DISPROVED__, or __UNKNOWN__.

Input & Output Example:
Facts:
- All birds have feathers.
- Penguins are birds.
- Feathers provide insulation.

Conclusion: *Penguins can maintain their body temperature.*

LLM Reasoning Output: Penguins are birds, all birds have feathers, and feathers provide insulation. Therefore, penguins can maintain their body temperature.

Label Output: __PROVED__ **True Answer:** __PROVED__

Baseline 2 Template: Chain of Thought (CoT)

Prompt Template:
Here is the Hypothesis: {conclusion}
Now These are the 'facts': {facts}
Please carefully evaluate the relationship between the facts and the hypothesis. Let's think step by step. Return UNKNOWN if the facts are insufficient to make a definitive conclusion. Return __PROVED__ only if the facts support the hypothesis. Return __DISPROVED__ only if the facts contradict the hypothesis. Output Conclusion: __PROVED__, __DISPROVED__, or __UNKNOWN__.

Input & Output Example:
Facts:
- If it rains, the ground gets wet.
- If the ground gets wet, plants grow better.
- It is raining today.

Conclusion: *Plants will grow better today.*

LLM Reasoning Output: Step 1: It is raining today (given fact). Step 2: If it rains, the ground gets wet (given fact). Step 3: Therefore, the ground gets wet today (from Step 1 and Step 2). Step 4: If the ground gets wet, plants grow better (given fact). Step 5: Therefore, plants will grow better today (from Step 3 and Step 4).

Label Output: __PROVED__ **True Answer:** __PROVED__

Baseline 3 Template: Few-shot Learning

Prompt Template:
Example 1: Hypothesis: Water boils at 100°C. Facts: At standard atmospheric pressure, water boils at 100°C. Output: __PROVED__
Example 2: Hypothesis: The sun rises in the west. Facts: The sun rises in the east every day. Output: __DISPROVED__
Here is the Hypothesis: {conclusion}
Now These are the 'facts': {facts}
Please carefully evaluate the relationship between the facts and the hypothesis. Return UNKNOWN if the facts are insufficient to make a definitive conclusion. Return __PROVED__ only if the facts support the hypothesis. Return __DISPROVED__ only if the facts contradict the hypothesis. Output Conclusion: __PROVED__, __DISPROVED__, or __UNKNOWN__.

Input & Output Example:
Facts:
- All mammals are warm-blooded.
- Dogs are mammals.
- Warm-blooded animals maintain constant body temperature.

Conclusion: *Dogs maintain constant body temperature.*

LLM Reasoning Output: Following the examples, dogs are mammals, all mammals are warm-blooded, and warm-blooded animals maintain constant body temperature. Therefore, dogs maintain constant body temperature.

Label Output: __PROVED__ **True Answer:** __PROVED__

Baseline 4 Template: Tree of Thought (ToT)

Prompt Template (Multi-step Process):
Step 1: Generate Multiple Reasoning Paths Here is the Hypothesis: {conclusion}
Now These are the 'facts': {facts}
Generate 3 different reasoning paths to evaluate this case. Each path should consider different aspects or perspectives:
Step 2: Evaluate Each Path Original Question: {original_prompt}
Reasoning Path: {thought}
Rate this reasoning path from 1-10 (1=very poor, 10=excellent) and explain why:
Step 3: Select Best Path and Generate Final Answer Based on this reasoning path: {best_thought}
Original Question: {original_prompt}
Provide the final answer: __PROVED__, __DISPROVED__, or __UNKNOWN__

Input & Output Example:
Facts:
- All metals conduct electricity.
- Copper is a metal.
- If something conducts electricity, it can be used in wires.

Conclusion: *Copper can be used in wires.*

LLM Reasoning Output:
Path 1: Copper is a metal → All metals conduct electricity → Copper conducts electricity → Can be used in wires. (Score: 9/10)
Path 2: Consider material properties → Copper has conductivity → Suitable for wires. (Score: 7/10)
Path 3: Direct application → Copper wires exist → Therefore can be used. (Score: 6/10)
Best Path: Path 1. Final Answer: __PROVED__

Label Output: __PROVED__ **True Answer:** __PROVED__

Baseline 5 Template: Plan & Solve

Prompt Template (Two-step Process):
Step 1: Create Plan Here is the Hypothesis: {conclusion}
Now These are the 'facts': {facts}
Before solving this problem, let's create a detailed step-by-step plan:
1. First, we need to... 2. Then, we should... 3. Finally, we will...
Please create a comprehensive plan for evaluating this case:
Step 2: Execute Plan Original Question: {original_prompt}
Plan: {plan}
Now let's execute this plan step by step. Follow the plan carefully and provide the final answer: __PROVED__, __DISPROVED__, or __UNKNOWN__

Input & Output Example:
Facts:
- All plants need sunlight to grow.
- Trees are plants.
- If something needs sunlight, it requires light energy.

Conclusion: *Trees require light energy.*

LLM Reasoning Output:
Plan: 1. Identify that trees are plants. 2. Apply the rule that all plants need sunlight. 3. Connect sunlight to light energy. 4. Conclude that trees require light energy.
Execution: Step 1: Trees are plants (given). Step 2: All plants need sunlight (given). Step 3: Therefore, trees need sunlight. Step 4: Sunlight provides light energy, so trees require light energy.

Label Output: __PROVED__ **True Answer:** __PROVED__

Baseline 6: Self-Reflection (Step 1 - Initial Answer Generation)

Step 1: Initial Answer Generation Prompt Template
For Dataset1/2 (Facts-based Datasets):
Here is the Hypothesis: {conclusion}
Now These are the 'facts': {facts}
Please carefully evaluate the relationship between the facts and the hypothesis. Return UNKNOWN if the facts are insufficient to make a definitive conclusion. Return __PROVED__ only if the facts support the hypothesis. Return __DISPROVED__ only if the facts contradict the hypothesis. Output Conclusion: __PROVED__, __DISPROVED__, or __UNKNOWN__.
Please provide your initial answer with detailed step-by-step reasoning. Think carefully about the relationship between the facts and the hypothesis/answer.

For Dataset3/4 (Story-based Datasets):
Question: {question} Facts: {facts} Answer: {correct_answer}
Based on the facts provided, determine if they can: 1. Prove the answer is correct (return __PROVED__) 2. Disprove the answer (return __DISPROVED__) 3. Are insufficient to determine the answer's correctness (return __UNKNOWN__)
Output Format: Only the Label: __PROVED__, __DISPROVED__, or __UNKNOWN__.
Please provide your initial answer with detailed step-by-step reasoning. Think carefully about the relationship between the facts and the hypothesis/answer.

Baseline 6: Self-Reflection (Step 2 - Reflection)

Step 2: Reflection Prompt Template
Original Question: {original_prompt}
Your Initial Answer: {initial_answer}
Now, carefully reflect on your answer: 1. Are there any logical errors or gaps in your reasoning? 2. Did you consider all the given facts? 3. Is there any evidence that contradicts your conclusion? 4. Are there alternative interpretations you missed? 5. Is your confidence level justified?
Provide a critical reflection on your initial answer, pointing out any potential issues or improvements:

Baseline 6: Self-Reflection (Step 3 - Refinement)

Step 3: Refinement Prompt Template
Original Question: {original_prompt}
Your Initial Answer: {initial_answer}
Your Reflection: {reflection}
Based on your reflection, provide a refined final answer. If your initial answer was correct, confirm it. If there were issues, provide the corrected answer.
Final Answer: __PROVED__, __DISPROVED__, or __UNKNOWN__