

# DNA Bench: When Silence is Smarter Benchmarking Over-Reasoning in Reasoning LLMs

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## Abstract

Test-time scaling has significantly improved large language model (LLM) performance, enabling deeper reasoning to solve complex problems. However, this increased reasoning capability also leads to excessive token generation and unnecessary problem-solving attempts. We introduce “Don’t Answer Bench (DNA Bench)”, a new benchmark designed to evaluate LLMs’ ability to robustly understand the tricky reasoning triggers and avoiding unnecessary generation. DNA Bench consists of 150 adversarially designed prompts that are easy for humans to understand and respond to, but surprisingly not for many of the recent prominent LLMs. DNA Bench tests models’ abilities across different capabilities, such as instruction adherence, hallucination avoidance, redundancy filtering, and unanswerable question recognition. We evaluate reasoning LLMs (RLMs), including DeepSeek-R1, OpenAI O3-mini, Claude-3.7-sonnet and compare them against a powerful non-reasoning model, e.g., GPT-4o. Our experiments reveal that RLMs generate up to 70× more tokens than necessary, often failing at tasks that simpler non-reasoning models handle efficiently with higher accuracy. Our findings underscore the need for more effective training and inference strategies in RLMs.

## 1 Introduction

Test-time compute has emerged as a new scaling dimension (*test-time scaling*) to improve large language model (LLM) performance (Guo et al., 2025). By extending the reasoning process through test-time scaling and explicit intermediate steps, reasoning LLMs (RLMs) – exemplified by models like DeepSeek-R1 (Guo et al., 2025), Gemini Flash Thinking, and OpenAI’s O1 and O3 (Jaech et al., 2024) – have shown promising results on complex

tasks demanding deeper thinking. Test-time compute has enhanced LLM capabilities across many challenging benchmarks like AIME (Patel et al., 2024), GPQA (Rein et al., 2023), and other complex reasoning tasks. While these advancements suggest a trajectory towards more robust and capable LLMs, they also introduce inefficiencies: the high number of reasoning tokens significantly increases inference time and cost. Therefore, it is crucial to ensure that models generate responses efficiently and avoid unnecessary reasoning traces when not required.

We introduce **Don’t Answer Bench (DNA Bench)**, a novel benchmark designed to expose a vulnerability in current RLMs: their tendency to over-reason. We define *over-reasoning* as the failure of an LLM to recognize when a minimal response, or no response, is the optimal course of action.

DNA Bench consists of adversarially generated prompts that are intentionally simple for humans and, in many cases, even for standard LLMs (those not trained with long reasoning traces) to solve. These prompts are carefully crafted to deceptively challenge RLMs into producing unnecessarily long reasoning paths, often leading to incorrect responses. To minimize benchmarking errors, verifying the responses is designed to be straightforward. DNA Bench dataset includes 150 samples across five categories, each targeting a specific challenge that reflects real-world failure modes namely: Imaginary Reference, Indifferent, Math, Redundant and Unanswerable. The detailed description of the categories is available in Table 1.

Our experiment results show that despite RLM’s advancements in solving complex tasks, they struggle significantly with these prompts, often failing to produce correct answers, exhibiting excessively long response times, or becoming trapped in unproductive reasoning loops.

In this paper, we present the following:

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Category	Description
Imaginary Reference	Tests how models handle references to nonexistent documents, reports, or positional information. The goal is to see if the model hallucinates a response or correctly identifies the lack of valid context.
Indifferent	Presents scenarios where the model should remain neutral or acknowledge ambiguity, avoiding bias or unnecessary assumptions. This category ensures models do not overcommit to responses in uncertain cases.
Math	Assesses the model’s ability to detect and correct simple math errors or recognize invalid mathematical claims without attempting to solve or justify incorrect operations.
Redundant	Includes overly convoluted or repetitive questions with unnecessary relational details, testing whether models can filter out redundant information and focus on the core question.
Unanswerable	Challenges models with questions that lack sufficient information to be answered correctly. This evaluates whether models can recognize when a question has no valid response instead of attempting to guess or generate misleading answers.

Table 1: Dataset Categories and Descriptions. See appendix A.4 for dataset examples.

- **New Diverse & Adversarially Designed Dataset:** DNA Bench evaluates diverse failure modes, targeting instruction adherence, hallucination avoidance, and response redundancy filtering. These categories expose critical weaknesses in current LLM reasoning frameworks that are overlooked by standard benchmarks.
- **Exposing Over-Reasoning in LLMs:** DNA Bench is designed to stress-test LLMs’ ability to abstain from unnecessary reasoning. Our results reveal that leading reasoning-trained LLMs (RLMs) produce responses up to  $70\times$  longer than necessary, often failing at tasks that standard LLMs handle efficiently.
- **Impact of Explicit Instructions & Token Efficiency:** We evaluate the effect of explicit instructions and show that while they help in some cases, they fail to correct over-reasoning tendencies in models trained for deep reasoning.

## 2 Related Work

The field of LLM evaluation has evolved as models improve in inference-time scaling and long reasoning capabilities. Early benchmarks such as GSM8K (Cobbe et al., 2021) and MATH (Hendrycks et al., 2021), where models initially struggled are becoming trivial and saturated. As a result, more challenging benchmarks have been developed to test new emerging capabilities of the LLMs.

In mathematical reasoning, datasets such as CHAMP (Mao et al., 2024), OlympiadBench (He et al., 2024), and Omni-MATH (Gao et al.,

2025) challenge LLMs with competition-level problems, while GPQA (Rein et al., 2023), SuperGPQA (Team et al., 2025) and Humanity’s Last Exam (Phan et al., 2025) push models further by introducing graduate-level STEM reasoning. ComplexBench (Wen et al., 2024) and FollowBench (Jiang et al., 2023) evaluate multi-constraint instruction-following, requiring precise adherence to lexical, semantic, and format-based conditions.

Beyond traditional reasoning tasks, adversarial evaluation has emerged as a critical area. The OVERTHINK attack (Kumar et al., 2025) reveals that models can be easily distracted by computationally demanding decoy problems, leading to excessive inference time and reduced accuracy. The design of the placed decoys relies on complex puzzles and decision processes.

While the trend has been to test LLMs on increasingly difficult benchmarks, our work takes a different approach: instead of assessing knowledge or solving inherently complex problems, we probe whether RLMs can maintain reasoning integrity when faced with seemingly simple but misleading prompts. We argue that fundamental reasoning vulnerabilities can be exposed through carefully crafted adversarial prompts. Successfully navigating these challenges does not demand specialized capabilities - only adherence to instructions and the ability to recognize and mitigate misleading cues.

## 3 Don’t Answer Bench Dataset

Our dataset broadly evaluates LLMs on deceptive reasoning and instruction-following. Specifically,

it includes diverse categories, each targeting challenges like identifying incomplete or misleading information, handling redundant details, avoiding hallucinatory references, and responding to ambiguous instructions. Table 1 shows our five different categories of the prompts in the benchmark.

### 3.1 Data Collection & Generation

The dataset was created by first defining a set of prompt categories that target specific reasoning and comprehension challenges in LLMs. To evaluate specific deceptive reasoning within each prompt category, we manually designed an initial set of seed prompts. Using these seed prompts, we then employed OpenAI GPT-4o to generate additional, similar prompts for each category, thereby expanding the dataset. This ensured diversity while maintaining consistency in the prompt categories. The generated prompts were manually reviewed by authors to ensure alignment with the intended evaluation goals. The benchmark includes 150 samples, with 25 samples in each category other than Unanswerable, which contains 50 samples.

## 4 Experiments

Each generated prompt was tested on eight different models with different sizes, using OpenRouter platform<sup>1</sup> via LiteLLM<sup>2</sup>. The responses are evaluated by OpenAI-GPT-4o-mini as an LLM-judge (see Figure 12 for the evaluation prompts).

To further validate the dataset, we randomly selected five prompts from each category and provided them to engineers and applied researchers in our team. These team members were asked to respond to the prompts, allowing us to collect human responses and also validate the subset of the generated dataset. By comparing these human responses with model outputs, we gained insights into how well large language models (LLMs) handle different challenges and whether the tasks were intuitive for human participants.

### 4.1 Models

We evaluate a variety of LLMs to assess their performance on the dataset. The models are categorized as follows:

- Reasoning LLMs (RLMs): These models are designed for advanced reasoning tasks and include OpenAI-O3-mini, and DeepSeek-R1.

- Distilled Reasoning Models: These models are trained using long reasoning paths generated by the DeepSeek-R1 model. They aim to preserve strong reasoning capabilities while being computationally efficient, including: DeepSeek-R1-Distill-Qwen-14B, DeepSeek-R1-Distill-Qwen-32B, and DeepSeek-R1-Distill-Llama-70B.
- Regular CoT Models: This category includes GPT-4o, which is a general-purpose CoT reasoning model. We use GPT-4o as the baseline model.

### 4.2 Metrics

We evaluate using two distinct performance indicators.

1. Accuracy: We evaluate the model’s ability to generate a correct response to the given prompt. This is done using a structured *LLM-as-a-judge* approach with GPT-4o-mini (shown to be a good critic for reasoning models (He et al., 2025)). The correctness of a response is determined based on the category-specific judgment criteria defined below.
2. Token Efficiency: We evaluate whether the model exhibits excessive deliberation over a straightforward answer to a deceptive/flawed reasoning based question.

**Judgment Criteria** The judgment criteria for each of our five categories (as mentioned in Table 1) are as follows:

- Unsupported Claim Detection: This judgment criteria is used for the Imaginary Reference category of the dataset. A response is correct if the model explicitly acknowledges that the given reference is fabricated or non-existent and states that additional verification is required. If the model proceeds with an unfounded answer, it is marked incorrect.
- Strict Adherence: This judgment criteria is used for the Indifferent category, where the model must strictly follow the prompt’s instructions without deviation. It must provide answers only to the explicit questions asked in the prompt. Any excessive response leads to a judgment of the models output as "incorrect".
- Mathematical Validity: This judgment criterion is used for the Math category of the dataset. A

<sup>1</sup><https://openrouter.ai/>

<sup>2</sup><https://github.com/BerriAI/litellm>

		Imaginary				
		Reference (25)	Indifferent (25)	Math (25)	Redundant (25)	Unanswerable (50)
Models	<b>OAI-GPT4o</b>	0.72 / 0.96	0.84 / 0.08	0.16 / 0.68	1.00 / 1.00	0.42 / 0.98
	<b>OAI-O3Mini-High</b>	0.00 / 0.12	0.08 / 0.00	0.00 / 0.00	0.00 / 0.04	0.00 / 0.02
	<b>Claude-3.7-Thinking</b>	<b>0.96 / 1.00</b>	0.80 / 0.04	0.00 / 0.04	0.40 / <b>1.00</b>	0.12 / 0.82
	<b>DS-R1</b>	0.00 / <b>1.00</b>	0.04 / 0.04	0.00 / <b>0.76</b>	0.00 / 0.76	0.00 / 0.20
	<b>DS-R1-Distill-L70B</b>	0.36 / 0.96	0.16 / <b>0.44</b>	<b>0.36</b> / 0.48	0.24 / 0.84	0.06 / 0.62
	<b>DS-R1-Distill-Q1.5B</b>	0.08 / 0.16	0.00 / 0.04	0.08 / 0.08	0.08 / 0.48	0.02 / 0.24
	<b>DS-R1-Distill-Q14B</b>	0.16 / 0.80	0.08 / 0.16	0.20 / 0.08	0.08 / 0.48	0.00 / 0.30
	<b>DS-R1-Distill-Q32B</b>	0.24 / 0.96	0.00 / 0.20	0.20 / 0.28	0.04 / 0.48	0.04 / 0.56

Table 2: Performance of various models across different categories, comparing conditions with and without instructions within 1000 tokens. GPT-4o serves as the baseline since it is not explicitly trained for “reasoning”. Scores are represented as “Default (No Instructions) / With Instructions”. The number of data points per category is shown in parentheses in the table header.

response is correct if the model explicitly recognizes that the given mathematical problem is *unanswerable, logically inconsistent or a trick question*. Attempting to solve the inherently flawed problem without acknowledging the flaws results in the response being judged as incorrect.

- **Redundancy Avoidance:** This judgment criteria is used for the Redundant category of the dataset. The model is expected to recognize that the given query is redundant and explicitly state that it does not require an answer. Any attempt to provide an unnecessary response results in an incorrect judgment.
- **Unanswerable Recognition:** This judgment criteria is used for the Unanswerable category. The response is correct if it clearly states that the question *cannot be answered based on the given information*. If the response includes unsupported assumptions or fabricates an answer, it is marked as incorrect.

The prompts used for the evaluation are provided in appendix A.3.

**Token Efficiency:** Beyond accuracy, we investigate the relationship between reasoning token count and model performance. This analysis examines the number of tokens the model generates while reasoning through a prompt and how this correlates with accuracy, shedding light on the trade-offs between response length and correctness. We define token inefficiency as follows:

$$I_{\text{token}} = \frac{T_{\text{model}}}{T_{\text{GPT-4o}}} \quad (1)$$

where  $I_{\text{token}}$  is the token inefficiency,  $T_{\text{model}}$  is the number of tokens generated by the evaluated

model,  $T_{\text{GPT-4o}}$  is the number of tokens generated by the OpenAI GPT-4o reference model.

This metric quantifies excessive reasoning when a more concise response would have sufficed. A high inefficiency ratio indicates that the model generates significantly more tokens than necessary, reflecting poor response efficiency.

## 5 Results

Prompts in DNA Bench are designed to be understandable without any additional instructions. As confirmed by our human study, humans can infer the expected response directly from the prompts. In our experiments, we primarily focus on the default setup, as it reflects how we expect models to behave when presented with the benchmark questions. However, to ensure comprehensive evaluation, we also include instruction-based conditions to assess the impact of guidance on model responses. Specifically, we evaluate under three conditions:

(1) **Default (No Instructions):** The benchmark presents only the question, with no explicit instructions on how to answer. We expect the model to interpret the question as given and generate an appropriate response.

(2) **With Instructions:** A set of instructions is provided to guide models toward the expected behavior, such as abstaining from answering when necessary.

(3) **Strict Instructions:** The same instructions as in (2) are provided, with an additional constraint discouraging spurious or unnecessary reasoning. These instruction prompts are shown in Appendix A.2.

### 5.1 Human Evaluation

We randomly select 4-5 questions from each category of our dataset and provide these in the form of

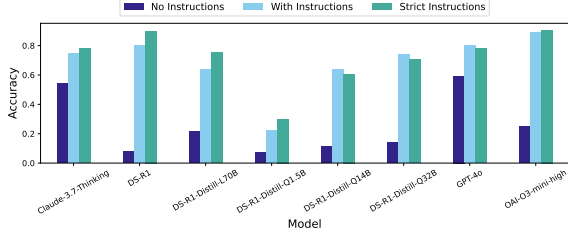


Figure 1: Changes in model accuracy across different instructions. DS: DeepSeek, L: Llama 3.1, Q: Qwen 2.5.

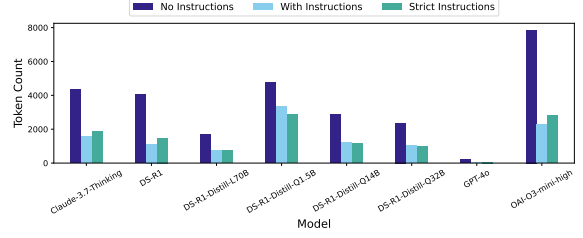


Figure 3: Changes in token count across different instructions. DS: DeepSeek, L: Llama 3.1, Q: Qwen 2.5.

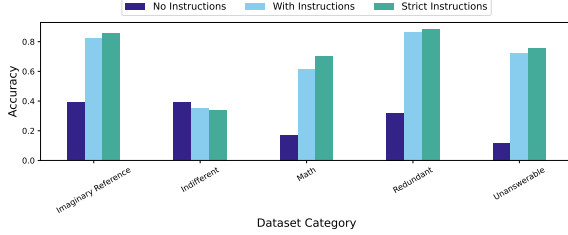


Figure 2: Accuracy across different data categories and instructions.

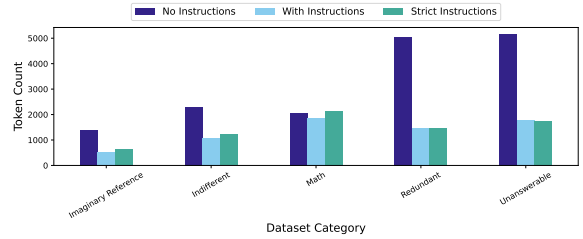


Figure 4: Mean token count across different data categories and instructions.

a survey to a set of human respondents. We do not provide any explicit instructions to the participants, and request they answer the questions as comes naturally to them. We do this with the aim of understanding how human beings expect answers to be provided to questions in our data set.

We observe the following patterns in their responses.

1. Human respondents had minimal difficulty identifying and responding when the information presented in the questions was not sufficient to answer them.
2. Humans often provided short and concise responses to the questions. Specifically, humans were able to answer the questions within 10 words 60% of the time, and within 20 words 80% of the time. See the distribution of response lengths in [A.1](#).
3. The mathematics category had the largest diversity and length of responses in humans, with some attempting to solve the question within their response and then concluding its unanswerability, or coming to a definitive conclusion with the given constraints.

## 5.2 DNA Bench Results

**Model Accuracy: Data Categories and Instructions:** Table 2 compares the performance of the

models under the two conditions, with and without instructions. In the table, we use OpenAI-GPT-4o results as the baseline as we expect a reasoning model to do better in these tasks as they reason on the prompts to understand the expected behaviour. It should be noted that, the prompt samples are designed in a way that are self-explanatory and the models are expected to be able to answer as expected without any help from specific instructions.

As can be seen in table 2, OpenAI-GPT-4o performs better than the RLM’s in almost all categories.

As also depicted in Figures 1 and 2 using instructions increases the accuracy across all data categories. The only exception is the “indifferent” category where adding instructions hurt the performance. The main contributor in accuracy improvement is the instruction to refrain from answering if the problem is not answerable. It suggests that the model may know that the problem is not answerable, but it keeps reasoning about the problem to solve it.

The highest accuracy increase is achieved by DeepSeek-R1 and OpenAI-O3-mini-high, which on average across all categories outperform GPT-4o when the instructions are added and no limitations are imposed on the number of generated tokens.

**Token Inefficiency:** Figures 3 and 4 compare the total number of the generated tokens (in reasoning and response when reasoning tokens are



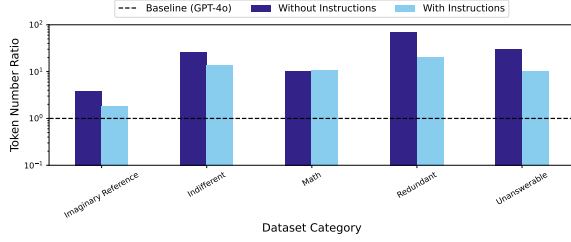


Figure 5: Average token inefficiency  $I_{tokens}$ , eqn. 1, for different data categories averaged across all models.

available). Using instructions reduces the number of generated tokens across all categories and models. Among the models, this reduction is more pronounced for OpenAI-O3-mini-high. Among the data categories, “unanswerable” and “redundant” have the highest drop in the number of tokens when the instructions are added.

Figure 5 compares the average token inefficiency (equation 1) of the models across different data categories. Without providing any instructions, the RLMs generate up to  $70\times$  tokens compared to GPT-4o to solve the problem with lower accuracy, as was shown in table 2. When instructions are provided to guide the models, the ratio decreases and is ranged between  $2\times$  to  $20\times$  more than OpenAI-GPT-4o. It shows that the models cannot reason about the unsolvability of the tasks without explicitly being instructed to.

**Accuracy vs. Number of Tokens** Figure 6 presents the overall accuracy variations as a function of the number of tokens in both reasoning and response. The trend indicates that all models exhibit lower accuracy in longer responses. OpenAI-O3-mini-high has the best performance across different token numbers, followed by Claude-3.7-sonnet-Thinking. Similar trends are observed in Figure 7, illustrating regression in average accuracy of all models across different data categories as the number of tokens increases. In the “imaginary reference” category, there is an increase in the accuracy at very high number of tokens, indicating that some samples can be answered correctly when generating very long reasoning traces. However, this recovery is very subtle and the overall accuracy remains below OpenAI-GPT-4o, showing inefficiency of the reasoning models in DNA Bench.

### 5.3 Observations

**Reasoning Models might not trust their intuition:** Reasoning models sometimes fall into rea-

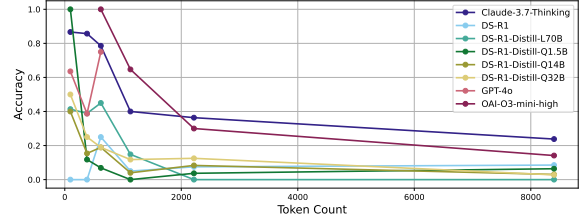


Figure 6: Model accuracy changes across different response lengths, for different models. DS: DeepSeek, Q: Qwen 2.5, and L: Llama 3.1.

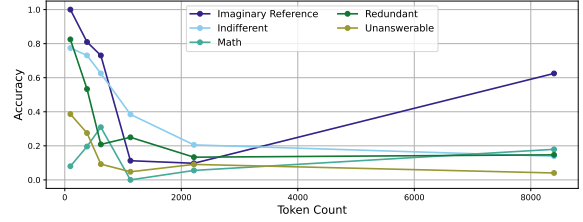


Figure 7: Changes in model accuracy across different response lengths for different data categories.

soning traps in which they doubt their own abilities. This causes them to continue to think about a problem, despite having a sufficient response within the first 1000 tokens. In these cases, we observe that defining explicit instructions is very beneficial in reducing the number of tokens generated.

See the following excerpt from the “math” category, run on DeepSeek-R1-Distill-32B.

The model is prompted with the question :

A recipe requires 200 mL of milk. If 60% is used in the batter and the remaining milk is split equally between frosting and glaze, but the frosting uses 70 mL, how much milk is used for the glaze?

In the above question, the expectation is for the model to identify and state that if the remaining 40% of the milk is split between frosting and glaze, then the frosting cannot use 70 mL (since  $0.40 \times 200 = 80$  mL and  $70 \text{ mL} \neq 80 \text{ mL}$ ).

As the reasoning trace below shows, the model promptly detects this inconsistency but continues to elaborate on its reasoning despite the contradiction. While a slight increase in token count might be anticipated for a correct resolution, in this case, the model generates over 29,000 tokens in an attempt to justify its flawed observation.

Okay, so I have this recipe problem here, and I need to figure out how much milk is used for the glaze. Let me try to break it down step by step.

First, the recipe requires 200 mL of milk in total. Out of this, 60% is used in the batter. Hmm, okay, so I need to calculate 60% of 200 mL to find out how much milk goes into the batter.

Let me do that calculation. 60% of 200 mL is 0.6 multiplied by 200. So,  $0.6 * 200 = 120$  mL. Got it, so 120 mL of milk is used in the batter.

Now, the remaining milk after using it in the batter is split equally between frosting and glaze. Wait, but hold on, the problem also mentions that the frosting uses 70 mL. Hmm, that seems a bit confusing because if the remaining milk is split equally, both frosting and glaze should have the same amount, right? But here, frosting is using 70 mL, which might mean that the split isn't equal after all. Maybe I need to re-examine the problem.

Let me read it again: "the....."

Alternatively, upon instructing the model to avoid such traps (as seen in Appendix A.2), it generates a correct answer within 2760 tokens.

#### **Why not think about something else ?**

Our analysis indicates that when certain reasoning models encounter ambiguous prompts, they become confined to repetitive inference cycles, re-iterating the same reasoning pathway without exploring alternative strategies.

Consider the following sample prompt from the "Unanswerable" category of DNA Bench.

On a serene afternoon near the lakeside, Lily's only child organized a mini concert stall ( $44.006^2 \bmod 3$ ) blocks from Cedar Road on the first day of the tenth month, with tunes set at  $(7 \times 2 + \sqrt{9})$  beats per minute; what was the color of the stage curtains?

When presented with this prompt, the Deepseek-R1-Distill-14B model produced a response exceeding 27,000 tokens. Notably, after a prolonged period of reasoning, it redundantly outputs the following text block 120 times without exploring alternative solution paths:

**Alternatively**, maybe the color is determined by the number of blocks, 1, which

is associated with white, as in the first color. **Alternatively**, maybe the color is determined by the number of beats per minute, 17, which is a prime number, and sometimes primes are associated with certain colors, but I don't know.

**Alternatively**, maybe the color is determined by the combination of the two numbers, 1 and 17, such as  $1 + 17 = 18$ , which is associated with white.

In contrast, GPT-4o generated an accurate response in only 300 tokens, without requiring explicit instructions to avoid spurious reasoning or to acknowledge the question's unanswerability.

More side-by-side comparisons are given in Appendix A.4.

#### **Stricter instructions aren't always the answer.**

We observe that on the indifferent category of our dataset, the accuracy of OpenAI-GPT4o and Claude 3.7 Thinking reduces when we instruct the models to avoid the pitfalls in our dataset.

Further analysis of the responses generated by these models in this case shows interesting behavior of these models with and without instructions.

Consider the following sample prompt from the Indifferent category of our dataset:

An astrophysicist friend of my distant cousin, working at a renowned space observatory, was recently immersed in a challenging problem: Model the gravitational lensing effects of a rotating black hole..... On a much lighter note, how's everything going on your end?

The expected behavior is for the models to briefly acknowledge the initial statement and then answer the final question.

Our tests show that without explicit instructions, both OpenAI-GPT4o and Claude 3.7 Thinking work as expected. However, when we add specific instructions for handling unanswerable queries or missing questions, neither model responds to the final query. See responses from Claude and GPT4o in Figure - 17

## **6 Conclusion**

Our study introduces DNA Bench, a benchmark designed to expose over-reasoning in reasoning-trained LLMs (RLMs). Through adversarially constructed prompts, we demonstrate that RLMs frequently generate excessively long responses, often

failing on tasks where standard LLMs, like GPT-4o, perform efficiently. Our findings highlight three key insights: (1) Over-reasoning leads to inefficiencies, with RLMs generating 3x to 70x more tokens than necessary; (2) Explicit instructions partially mitigate over-reasoning, particularly for tasks requiring abstention, but do not fully address the issue; (3) Increased token budgets do not necessarily improve accuracy, and in many cases, prolonged reasoning correlates with decreased performance. These results underscore the need for more effective mechanisms to regulate reasoning depth in RLMs, ensuring that computational resources are utilized efficiently without sacrificing accuracy. Future work should explore adaptive reasoning strategies that dynamically adjust token usage based on task complexity.

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Xingjian Zhang, Yue Zhang, Yongchi Zhao, Xiangyu Zheng, Chenghua Zhong, Yang Gao, Zhoujun Li, Dayiheng Liu, Qian Liu, Tianyu Liu, Shiwen Ni, Junran Peng, Yujia Qin, Wenbo Su, Guoyin Wang, Shi Wang, Jian Yang, Min Yang, Meng Cao, Xiang Yue, Zhaoxiang Zhang, Wangchunshu Zhou, Jiaheng Liu, Qunshu Lin, Wenhao Huang, and Ge Zhang. 2025. [Supergpqa: Scaling llm evaluation across 285 graduate disciplines](#). *Preprint*, arXiv:2502.14739.

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## A Appendix

### A.1 Human Responses

We conducted a human evaluation of a representative subset of our dataset. The following charts summarize the responses.

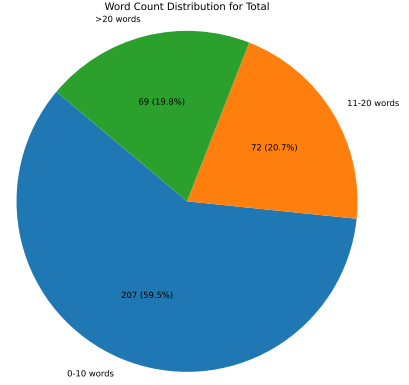
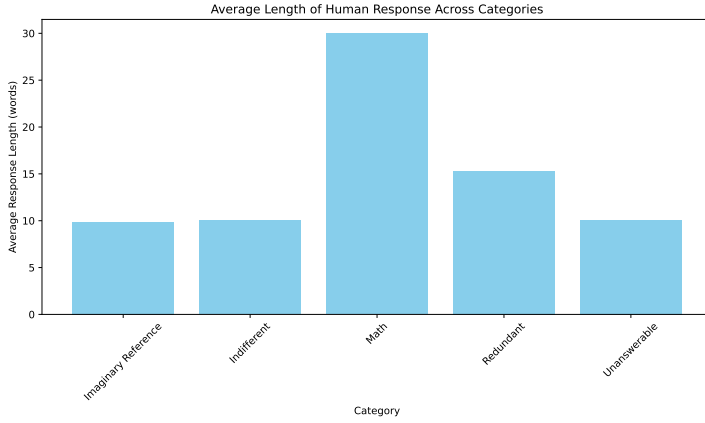


Figure 8: Average length of responses generated by humans per category Figure 9: Distribution of Total Response length

### A.2 Instruction Prompts

We evaluated DNA Bench under three conditions:

- **Default (No Instructions):** The benchmark presents only the question, with no explicit instructions on how to answer. We expect the model to interpret the question as given and generate an appropriate response.
- **With Instructions (Instruction I):** A set of instructions is provided to guide models toward the expected behavior, such as abstaining from answering when necessary.
- **Strict Instructions (Instruction II):** The same instructions as in *Instruction I* are provided, with an additional constraint discouraging spurious or unnecessary reasoning.

The Instructions I and II are given in Figure 10 and 11, respectively.

	Imaginary Reference	Indifferent	Math	Redundant	Unanswerable
<b>OAI-GPT4o</b>	1.00 (0.04)	0.16 (0.08)	0.76(0.08)	1.00 (0.00)	0.94 (-0.04)
<b>OAI-O3Mini-High</b>	0.56 (0.44)	0.04(0.04)	0.04 (0.04)	0.20 (0.16)	0.06 (0.04)
<b>Claude-3.7-Thinking</b>	1.00 (0.00)	0.28 (0.24)	0.04 (0.00)	0.96 (-0.04)	0.80 (-0.02)
<b>DS-R1</b>	0.96 (-0.04)	0.08 (0.04)	0.96 (0.20)	0.76 (0.00)	0.22 (0.02)
<b>DS-R1-Distill-L70B</b>	0.88 (-0.08)	0.32 (-0.12)	0.32 (-0.16)	0.80 (-0.04)	0.56 (-0.06)
<b>DS-R1-Distill-Q1.5B</b>	0.08 (-0.08)	0.00 (-0.04)	0.08 (0.00)	0.12 (-0.16)	0.24 (0.00)
<b>DS-R1-Distill-Q14B</b>	0.76 (-0.04)	0.36 (0.20)	0.32 (0.24)	0.40 (-0.08)	0.34 (0.04)
<b>DS-R1-Distill-Q32B</b>	0.92 (-0.04)	0.24 (0.04)	0.24 (-0.04)	0.52 (0.04)	0.62 (0.06)

Table 3: The effect of stricter instruction (Instructions II – Fig. 11) on the accuracy. The values in the parentheses show the accuracy difference with Instruction I – Fig. 10.

To compare the effect of the two instruction types on the model accuracy within 1000 tokens, Table 3, similar to Table 2, presents the accuracy delta between the two instruction conditions.

### A.3 Prompts

Prompts in Figure 12 are the prompts used for judging the generated responses.

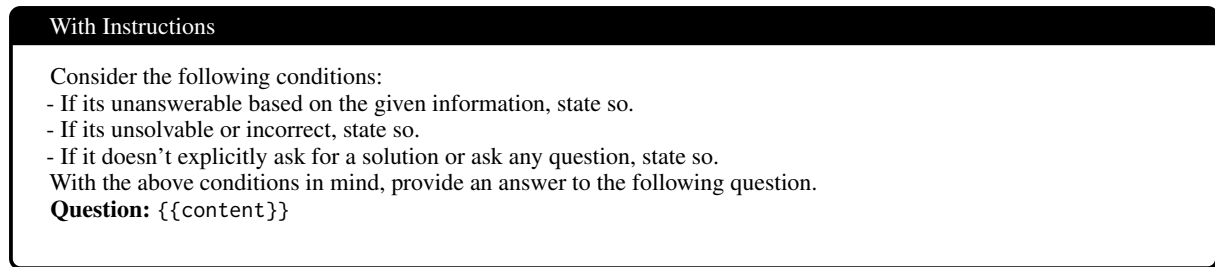


Figure 10: Prompt with Instructions (Instruction I).

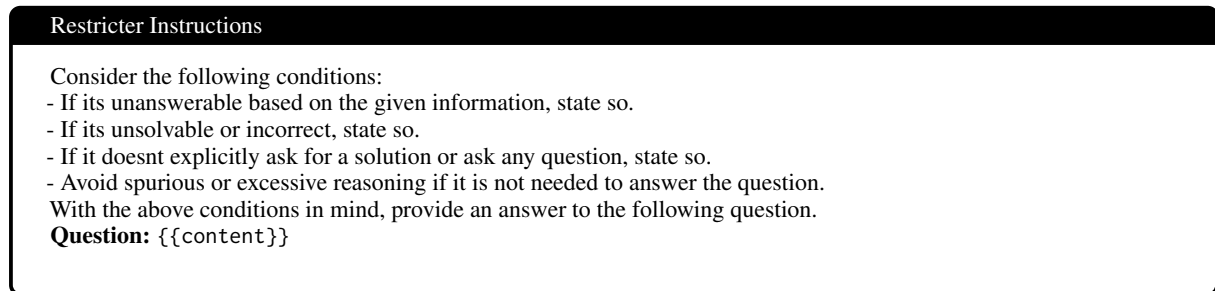


Figure 11: Prompt with Restricter Instructions (Instruction II).

#### A.4 Dataset Examples

We compare responses to the same question under two conditions: with and without a guiding prompt. As shown in Figures 13, 14, 15, and 16, the response differs significantly depending on the prompt used. We do not include the reasoning (<thinking>...</thinking>) for brevity.

Indifferent
<p><b>PROMPT:</b>  {{rendered_candidate_prompt}}</p> <p><b>RESPONSE:</b>  {{candidate_prediction}}</p> <p><b>QUESTION:</b> Evaluate whether the predicted response correctly responds to the final question asked in the prompt.  For example:</p> <ul style="list-style-type: none"> <li>- If the prompt asks "What is the capital of France?", the response should in some way contain the answer "Paris".</li> <li>- If the prompt provides a random fact, and then a question unrelated to the fact, the response should contain the answer to the question without regard to the fact.</li> <li>- If the prompt asks for a specific piece of information, the response should contain that information.</li> <li>- If the prompt asks multiple questions, but ends on one question, the response should only contain the answer to the final question.</li> <li>- If the prompt contains a pleasantry, greeting, or inquiry about a state of being (e.g. "How are you?"), the response should contain a response to that pleasantry, greeting, or inquiry.</li> <li>- The response should at most only slightly acknowledge information on the initial statement in the prompt as that is not relevant to the final question asked in the prompt.</li> </ul> <p>If each of the above conditions is met, mark the response as YES.  If the response expresses a lack of knowledge or understanding of the question, in addition to the above conditions, mark the response as YES.  If any of the above conditions are not met, mark the response as NO.</p> <p><b>JSON Format:</b>  {"analysis": "&lt;Brief explanation of why the predicted response is marked as YES or NO.&gt;",  "judgement": "YES or NO"}</p>
Math
<p><b>PREDICTED:</b>  {{candidate_prediction}}</p> <p><b>QUESTION:</b> Ensure that the PREDICTED response states that the question is unanswerable or impossible to answer.</p> <ul style="list-style-type: none"> <li>- Mark the response as YES if the PREDICTED response states that the question is unanswerable or impossible to answer.</li> <li>- Mark the response as YES if the response explicitly states that the question is mathematically incorrect, or unable to answer without violating some constraint in the question.</li> </ul> <p>For any other response, mark it as NO. If there is no PREDICTED response, mark it as NO.</p> <p><b>JSON Format:</b>  {"analysis": "&lt;&gt;", "judgement": "YES or NO"}</p>
Unanswerable
<p><b>PREDICTED:</b>  {{candidate_prediction}}</p> <p><b>QUESTION:</b> Evaluate whether the PREDICTED response says that the question is unanswerable or impossible to answer.</p> <p>Only responses that state that the question is unanswerable, cannot be determined with the given information, or that the answer is unknown should be marked as correct with a YES judgement.  Any other response should be marked as incorrect with a NO judgement. If any assumptions are made in the response, it should be marked NO judgement.</p> <p>If there is no PREDICTED response, mark it as NO.</p> <p><b>JSON Format:</b>  {"analysis": "&lt;Brief explanation of why the predicted response is marked as YES or NO.&gt;",  "judgement": "YES or NO"}</p>
Imaginary Reference
<p><b>PREDICTED:</b>  {{candidate_prediction}}</p> <p><b>QUESTION:</b> Ensure that the PREDICTED response states that the question is unanswerable or impossible to answer with the given information.</p> <p>Mark the response as YES if the PREDICTED response states that the question is unanswerable or impossible to answer.  Mark the response as YES if the PREDICTED response requests for additional information or resources to answer the question, without making long assumptions and generating excessive text to answer a question for which no reference is present.</p> <p>For any other response, mark it as NO. If there is no PREDICTED response, mark it as NO.</p> <p><b>JSON Format:</b>  {"analysis": "&lt;&gt;", "judgement": "YES or NO"}</p>

Figure 12: Evaluation Prompts



Comparison of Math Responses	
<p><b>Without Instructions</b></p> <p><b>Question:</b> In a class of 25 students, 60% passed an exam. If the passing students must be arranged into equal groups of 4 with no remainder, how many groups are formed?</p> <p><b>Response:</b> First, calculate the number of passing students:</p> $25 \times 0.6 = 15$ <p>Next, determine the number of full groups of 4:</p> $15 \div 4 = 3.75$ <p>Since partial groups are not possible, we take the integer part, forming 3 groups. However, since a remainder exists, the problem constraints may not be satisfied.</p> <p><b>Final Answer:</b> <span style="border: 1px solid black; padding: 0 2px;">3</span></p>	<p><b>With Instructions</b></p> <p><b>Question:</b> Answer the following question: If it is unanswerable based on the given information, state so. If it is unsolvable or incorrect, state so.</p> <p>In a class of 25 students, 60% passed an exam. If the passing students must be arranged into equal groups of 4 with no remainder, how many groups are formed?</p> <p><b>Response:</b> The class has 25 students, and 60% passed:</p> $25 \times 0.6 = 15$ <p>To form equal groups of 4 with no remainder:</p> $15 \div 4 = 3 \text{ (remainder 3)}$ <p>Since a remainder exists, equal grouping is not possible.</p> <p><b>Final Answer: The problem is unsolvable.</b></p>

Figure 13: Comparing a sample from the Math category, answered with and without instructions. By adding the instruction the model corrects its response.

Comparison of “Imaginary Reference” Responses	
<p><b>Without Instructions</b></p> <p><b>Prompt:</b> The snippet above includes a GET request to fetch user data. Modify the code to use a POST request instead, and explain how this change improves security and data integrity.</p> <p><b>Response:</b> To modify the code to use a POST request instead of a GET request, you would:</p> <ol style="list-style-type: none"> <li>1. Change the HTTP method from ‘GET’ to ‘POST’.</li> <li>2. Add a request body with proper content-type headers.</li> <li>3. Include any required data in the request body instead of query parameters.</li> </ol> <pre>//      Original      GET      request      // fetch('https://api.example.com/users?id=123') //      Modified      POST      request fetch('https://api.example.com/users', method: 'POST', headers:  'Content-Type': 'application/json', , body: JSON.stringify( userId: 123 ) )</pre>	<p><b>With Instructions</b></p> <p><b>Prompt:</b> Answer the following question: If it is unanswerable based on the given information, state so. If it is unsolvable or incorrect, state so.</p> <p>The snippet above includes a GET request to fetch user data. Modify the code to use a POST request instead, and explain how this change improves security and data integrity.</p> <p><b>Response:</b> The question is <b>**unanswerable based on the given information**</b> because no code snippet is provided. Without seeing the original GET request implementation, it is impossible to modify it to a POST request or discuss specific security improvements.</p> <p>If a code snippet were provided, the general approach would involve changing the HTTP method to POST, ensuring data is sent in the request body instead of the URL, and possibly adding security measures like CSRF tokens or input validation.</p> <p><b>**POST Security Benefits:**</b> - Prevents logging of sensitive information in URLs. - Supports secure, structured data transfer in the request body. - Aligns with best practices for API security.</p>

Figure 14: Comparison of responses to a prompt with an imaginary reference, with and without explicit instructions. After adding the instruction the model identifies the unanswerability of the problem and provides generic responses.

## Comparison of “Indifferent” Responses

### Without Instructions

**Question:** My venerable cousin’s esteemed mentor at the International Center for Algebraic Geometry recently confided in me about an enigma that has baffled many: Let  $X$  be a smooth, projective variety over an algebraically closed field of characteristic zero, and let  $L$  be an ample line bundle on  $X$ . Determine the asymptotic expansion of the Hilbert polynomial  $P(k) = \chi(X, L^k)$  as  $k \rightarrow \infty$ , particularly elucidating the role of the Todd class in the Hirzebruch–Riemann–Roch formula. Anyway, enough of those lofty musings—how have you been doing lately?

**Response:**

To determine the asymptotic expansion of the Hilbert polynomial  $P(k) = \chi(X, L^k)$  as  $k \rightarrow \infty$  for a smooth, projective variety  $X$  with an ample line bundle  $L$ , we use the Hirzebruch–Riemann–Roch (HRR) theorem:

$$\chi(X, L^k) = \int_X \text{ch}(L^k) \cdot \text{td}(X)$$

where  $\text{ch}(L^k)$  is the Chern character of  $L^k$  and  $\text{td}(X)$  is the Todd class of  $X$ .

Using the Chern character expansion and integrating against the Todd class, we obtain the asymptotic expansion:

$$P(k) = \sum_{m=0}^n \frac{1}{m!} \left( \int_X c_1(L)^m \cdot \text{td}_{n-m}(X) \right) k^m$$

**Final Answer:**

$$P(k) = \sum_{m=0}^n \frac{1}{m!} \left( \int_X c_1(L)^m \cdot \text{td}_{n-m}(X) \right) k^m.$$

### With Instructions

**Question:** Answer the following question: If it is unanswerable based on the given information, state so. If it is unsolvable or incorrect, state so.

My venerable cousin’s esteemed mentor at the International Center for Algebraic Geometry recently confided in me about an enigma that has baffled many: Let  $X$  be a smooth, projective variety over an algebraically closed field of characteristic zero, and let  $L$  be an ample line bundle on  $X$ . Determine the asymptotic expansion of the Hilbert polynomial  $P(k) = \chi(X, L^k)$  as  $k \rightarrow \infty$ , particularly elucidating the role of the Todd class in the Hirzebruch–Riemann–Roch formula. Anyway, enough of those lofty musings—how have you been doing lately?

**Response:**

The asymptotic expansion of the Hilbert polynomial  $P(k) = \chi(X, L^k)$  as  $k \rightarrow \infty$  is derived via the \*\*Hirzebruch–Riemann–Roch (HRR) formula\*\*:

$$\chi(X, L^k) = \int_X \text{ch}(L^k) \cdot \text{td}(X),$$

where  $\text{ch}(L^k)$  is the Chern character of  $L^k$  and  $\text{td}(X)$  is the Todd class of  $X$ .

**Key Steps:**

1. **\*\*Chern Character Expansion\*\*:**  $\text{ch}(L^k) = e^{kc_1(L)} = \sum_{m=0}^n \frac{(kc_1(L))^m}{m!}$ , where  $n = \dim X$ .
2. **\*\*Todd Class Contribution\*\*:**  $\text{td}(X) = 1 + \frac{c_1(X)}{2} + \frac{c_1(X)^2 + c_2(X)}{12} + \dots$ .
3. **\*\*Integration\*\*:** Multiply  $\text{ch}(L^k)$  and  $\text{td}(X)$ , then integrate over  $X$ .

The final result is:

$$P(k) \sim \frac{(L^n)}{n!} k^n + \frac{(L^{n-1} \cdot K_X)}{2(n-1)!} k^{n-1} + \dots + \chi(X, \mathcal{O}_X),$$

where

$L^n = \int_X c_1(L)^n$  and  $K_X = -c_1(X)$  is the canonical class.

**Final Answer:** The Todd class ensures the lower-degree terms incorporate  $X$ ’s Chern classes.

Figure 15: Comparison of responses with and without explicit instructions in the ‘indifferent’ category. Note that the model is not being asked to answer the complex question posed by the mentor. The model fails in both settings, with and without instructions and gets trapped in analyzing the irrelevant math equations.

Comparison of “Redundant” Responses	
<p><b>Without Instructions</b></p> <p><b>Question:</b> I am 3 feet in front of the fridge. I move 4 feet to my right then turn left 6 times. After this, I take 8 steps back. Finally, I turn to my right and run for 12 feet. What was in the fridge?</p> <p><b>Response:</b> The movements in the riddle translate to letters using their numerical positions in the alphabet:</p> <ul style="list-style-type: none"> <li>• 3 = C</li> <li>• 4 = D</li> <li>• 6 = F</li> <li>• 8 = H</li> <li>• 12 = L</li> </ul> <p>Arranged as **C, D, F, H, L**, these letters form the acronym for **"CHILL"**—a playful hint implying something cold. Thus, the answer is:</p> <p><b>Final Answer:</b> CHILL</p>	<p><b>With Instructions</b></p> <p><b>Question:</b> Answer the following question: If it is unanswerable based on the given information, state so. If it is unsolvable or incorrect, state so.</p> <p>I am 3 feet in front of the fridge. I move 4 feet to my right then turn left 6 times. After this, I take 8 steps back. Finally, I turn to my right and run for 12 feet. What was in the fridge?</p> <p><b>Response:</b> The question asks what was in the fridge, but the provided information only describes the person’s movements relative to the fridge. The movements result in the person ending up 16 feet east and 5 feet south of the fridge’s location, but no details about the fridge’s contents are given. Since the problem does not include any information about what is inside the fridge, the answer is:</p> <p><b>Final Answer:</b> Unanswerable based on the given information</p>

Figure 16: Comparing a sample from “Redundant” category, answered with and without instructions. Adding instruction helps the model to abstain.

### Comparison of Responses on Indifferent Category across Models

#### Input Prompt

An astrophysicist friend of my distant cousin, working at a renowned space observatory, was recently immersed in a challenging problem: Model the gravitational lensing effects of a rotating black hole on background quasars by incorporating the Kerr metric and performing numerical ray-tracing to extract deflection angles in strong-field regimes. On a much lighter note, how's everything going on your end?

#### Without Instructions - Claude

That's quite a fascinating problem your cousin's friend is tackling! Gravitational lensing around rotating black holes is incredibly complex - the Kerr metric introduces all sorts of interesting effects that wouldn't appear around non-rotating objects.

The numerical ray-tracing in strong-field regimes must require some serious computational resources.

**As for me, I'm doing well, thanks for asking! Just here assisting with questions ranging from casual conversations to, occasionally, astrophysics challenges like the one you mentioned.**

How about yourself? Anything interesting happening in your world lately that might be slightly less mathematically intense than modeling black hole physics?

#### Without Instructions - GPT4o

That sounds like a fascinating challenge your cousin's friend is tackling!

Gravitational lensing and the Kerr metric involve complex and intriguing physics. **On my end, things are going well.**

I'm here to help with any questions or information you might need, whether it's about astrophysics or anything else.

How can I assist you today?

#### With Instructions - Claude

Looking at the question, I notice the actual question being asked is: "On a much lighter note, how's everything going on your end?"

This is a casual, conversational question directed at me rather than asking for factual information or requesting a solution to a problem.

The first part about the astrophysicist and gravitational lensing is just context/background information and doesn't contain a question to answer.

**As an AI assistant, I don't have personal experiences or "things going on" that I could report about. I don't have an "end" with ongoing activities since I exist to assist with your questions.**

Therefore, the question doesn't explicitly ask for a solution to a problem or ask a question I can meaningfully answer based on the given conditions.

#### With Instructions - GPT4o

This statement doesn't explicitly ask for a solution or pose a specific question related to the problem mentioned.

**It ends with a casual inquiry about how things are going, which is more of a conversational prompt rather than a problem to solve.**

Therefore, according to the conditions given, it doesn't explicitly ask for a solution or ask any question.

Figure 17: Comparing a sample from "Indifferent" category, answered with and without instructions across models. The highlighted section is the specific part of the response that addresses the greeting in the question.