Decoding Answers Before Chain-of-Thought: Evidence from Pre-CoT Probes and Activation Steering

Anonymous Authors[1]

Abstract

As chain-of-thought (CoT) has become central to scaling reasoning capabilities in large language models (LLMs), it has also emerged as a promising tool for interpretability, suggesting the opportunity to understand model decisions through verbalized reasoning. However, the utility of CoT toward interpretability depends upon its faithfulness—whether the model's stated reasoning reflects the underlying decision process. We provide mechanistic evidence that instruction-tuned models often determine their answer before generating CoT. Training linear probes on residual stream activations at the last token before CoT, we can predict the model's final answer with >0.9 AUC on most tasks. We find that these directions are not only predictive, but also causal: steering activations along the probe direction flips model answers in over 50% of cases, significantly exceeding orthogonal baselines. When steering induces *incorrect* answers, we observe two distinct failure modes: *non-entailment* (stating correct premises but drawing unsupported conclusions) and *confabulation* (fabricating false premises). While post-hoc reasoning may be instrumentally useful when the model has a correct pre-CoT belief, these failure modes suggest it can result in undesirable behaviors when reasoning from a false belief.

1. Introduction

Large language models can externalize their reasoning through chain-of-thought, producing step-by-step rationales that appear interpretable to humans and can improve task performance (Wei et al., 2023). This makes CoT a promising vehicle for scalable interpretability and safety monitoring, as natural language is far easier to audit than latent activations.

However, the utility of CoT toward interpretability depends upon its *faithfulness*—whether the model's verbalized reasoning reflects its true decision-making process (Jacovi & Goldberg, 2020). This condition does not always hold. Prior work documents instances where models rationalize biased answers with convincing but misleading CoT (Turpin et al., 2023), and instances where larger models ignore their own CoT when producing final answers (Lanham et al., 2023; Gao, 2023). Successful operationalization of CoT for safety monitoring may depend on characterizing modes of unfaithfulness.

One way to reason about this is to consider optimization pressures toward unfaithfulness—i.e., which forms are expected given the training regime (nostalgebraist, 2024). Consider, for example, an intelligent model, trained to produce helpful, honest, harmless responses (Bai et al., 2022) that has been given a question so simple it could answer in a single forward pass. Now suppose, as in Lanham et al. (2023), the model is given a scratchpad with a mistake in the reasoning. Now the model must either respond with what it knows to be the correct answer, or the incorrect answer entailed by the incorrect chain-of-thought. The former is perhaps the preferred behavior, but it would constitute unfaithful reasoning.

We use *post-hoc reasoning* to refer to these instances where the model's answer is determined before the CoT, and call this answer the *pre-committed answer*.

Prior work has established evidence of post-hoc reasoning through primarily prompt-level experiments (Lanham et al., 2023; Arcuschin et al., 2025; Bao et al., 2024). For example, models might respond in the same way when their CoT is swapped with an incorrect CoT. These findings invite hypotheses about what *mechanistic phenomena* are involved in post-hoc reasoning.

Our experiments are sequenced in the following way.

Empirical premise (P0). Prior work has shown that on some reasoning tasks, models may "know" the answer prior to CoT and perform reasoning post-hoc. For example, models may respond correctly when CoT is removed, or replaced

[1]Anonymous Institution, Anonymous City, Anonymous Region, Anonymous Country. Correspondence to: Anonymous Author <anon.email@domain.com>.

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with a misleading CoT. We select datasets where CoT is differentially useful, and verify that our models exhibit this behavior on some tasks. In § 3.1 we compare the accuracy of our models with and without CoT, and in § 3.2 we evaluate model accuracy under two CoT interventions: removal (swapping with ellipses) and substitution (swapping with an incorrect, misleading CoT).

Hypotheses. Conditional on this premise, we test three hypotheses:

- **Representational pre-commitment (H1).** The model's final answer is encoded in pre-CoT activations in the residual stream, and is linearly decodable by a simple probe (§ 3.3).
- **Causal pre-commitment feature (H2).** The probe direction is not merely predictive but causal: steering activations along this direction shifts the model's answer far more than equally large orthogonal perturbations (§ 3.4).
- **Pathologies of unfaithfulness (H3).** When steered in the direction of the incorrect response, the model's verbalized reasoning will exhibit two patterns: (1) stating false premises to support the steered answer (*confabulation*) and (2) stating true premises but giving a conclusion that does not follow (*non-entailment*) (§ 3.5).

Interpretation. Given evidence for H1–H3, we consider whether the probe direction constitutes a causal representation of the pre-committed answer. We respond to alternative explanations, and argue that this interpretation is reasonable in § 4.1.

2. Methods

2.1. Models and Datasets

We evaluate five instruction-tuned models across two families—Gemma 2 (2B-it, 9B-it) (Team et al., 2024) and Qwen 2.5 Instruct (1.5B-it, 3B-it, 7B-it) (Qwen et al., 2025)—on four binary classification tasks spanning factual, logical, and social reasoning:

1. **Anachronisms**: Determine whether a statement about a historical event contains anachronisms or not (Suzgun et al., 2022).
2. **Logical Deduction**: Determine whether a conclusion follows from given premises (Suzgun et al., 2022).
3. **Sports Understanding**: Determine whether a statement about sports is plausible or implausible (Suzgun et al., 2022).
4. **Social Chemistry**: Determine whether a social interaction is acceptable or not (Forbes et al., 2021).

Each task is formatted as a binary classification task with four few-shot CoT demonstrations. Demonstrations follow consistent reasoning patterns and offer a reasoning template for the model to follow (Wei et al., 2023). Answer choices are presented as a choice between options A and B. The order of the contents of A and B is randomized to control for positional bias. Figure 1 shows an example prompt from the Sports Understanding task. Example questions for each task are shown in Appendix A.

Each dataset is split into 500 train and 500 test examples. Responses are parsed by extracting the final answer token ("(A)" or "(B)"). Where responses cannot be parsed, we report a failed generation. All outputs are generated by sampling at temperature 0.7.

Q: Is the following sentence plausible? "Kylian Mbappe went in studs up."

Answer choices:
(A) No, the sentence is implausible
(B) Yes, the sentence is plausible

Please verbalize how you are thinking about the problem, then give your answer in the format "The best answer is: (X)". It's very important that you stick to this format.

A: Let's think step by step:

Figure 1. Example prompt from the Sports Understanding task. The model generates its response starting from "Let's think step by step:".

2.2. Testing for CoT Sensitivity

These experiments establish the empirical premise (**P0**) that models often exhibit post-hoc reasoning on our tasks.

We evaluate how sensitive the model is to chain-of-thought in two ways:

Accuracy improvement due to CoT. We evaluate model accuracy with and without CoT. In the no-CoT examples, the model is instructed to respond only with the answer, including no reasoning. The in-context demonstrations for the no-CoT evaluation are the same as those for the CoT evaluation, but stripped of the CoT.

CoT intervention. Similar to Lanham et al. (2023), we intervene on the CoT and measure how sensitive the final answer is to CoT. For two models per model family (Gemma 2: 2B, 9B; Qwen 2.5: 1.5B, 7B) and each dataset, we randomly sample 50 test generations where the model was correct and implement two interventions:

1. **Ellipses.** Substitute the chain-of-thought with the string "...".

2. **Wrong CoT.** Modify the CoT to introduce a mistake that will imply the opposite answer.

The details of the intervention procedure are described in Appendix B.

2.3. Probing for Pre-Computed Answers

To determine if the final answer is linearly decodable pre-CoT (**H1**), we construct difference-of-means probes on the training set to predict the model's final answer from its activations before generating reasoning (Marks & Tegmark, 2024). Let t_0 denote the last pre-CoT token in the prompt (the colon in "Let's think step by step:"), and let $\mathbf{x}_{i,t_0}^{(\ell)}$ be the residual stream activation at layer ℓ and position t_0 for training example i. We partition training examples by their final answer $c \in \{\text{yes}, \text{no}\}$ and compute

$$\boldsymbol{\mu}_c^{(\ell)} = \frac{1}{|D_c|} \sum_{i \in D_c} \mathbf{x}_{i,t_0}^{(\ell)}, \qquad \mathbf{w}^{(\ell)} = \boldsymbol{\mu}_{\text{yes}}^{(\ell)} - \boldsymbol{\mu}_{\text{no}}^{(\ell)}.$$

For a held-out test example j, we compute the cosine similarity score

$$s_j^{(\ell)} = \cos\big(\mathbf{x}_{j,t_0}^{(\ell)}, \mathbf{w}^{(\ell)}\big),$$

and compute $\mathrm{AUC}^{(\ell)}$ over $\{(s_j^{(\ell)}, \text{label}_j)\}_j$,

where high $\mathrm{AUC}^{(\ell)}$ indicates that the final answer is linearly decodable from pre-CoT activations (Alain & Bengio, 2018; Hewitt & Liang, 2019; Hewitt & Manning, 2019; Belinkov, 2021).

2.4. Flipping Answers via Activation Steering

In this section, we test whether the probes identified in § 2.3 are merely correlational artifacts, or if they causally influence the final answer (**H2**).

To test this hypothesis, we intervene on the probe direction during CoT via contrastive activation addition (Turner et al., 2024; Rimsky et al., 2024). At inference time, for every forward pass and each decoding token position following the prompt $t > t_0$, we apply the following edit at layer $\ell^\star$:

$$\tilde{\mathbf{x}}_t^{(\ell^\star)} = \mathbf{x}_t^{(\ell^\star)} + \alpha\, \mathbf{w}^{(\ell^\star)},$$

where α is the steering coefficient (by convention, $\alpha > 0$ pushes toward "yes," $\alpha < 0$ toward "no"). The layer $\ell^\star$ is the one with the highest probe $\mathrm{AUC}^{(\ell)}$. We evaluate forced flips on two subsets of the test set: S_{yes} (examples the model initially answered "yes" correctly), where we sweep $\alpha \in \{0, -2, -4, \ldots, -20\}$, and S_{no} (initially "no" and correct), where we sweep $\alpha \in \{0, 2, 4, \ldots, 20\}$. Figure 2 schematizes this process.

Orthogonal-direction baseline. To distinguish causal influence from generic perturbation effects, we compare steering with $\mathbf{w}^{(\ell^\star)}$ to steering in a per-example random direction $\mathbf{r}_j$ that is orthogonal and norm-matched $\big(\langle \mathbf{r}_j, \mathbf{w}^{(\ell^\star)} \rangle = 0$ and $\|\mathbf{r}_j\| = \|\mathbf{w}^{(\ell^\star)}\|\big)$. If answer flips were merely a consequence of pushing activations off-manifold, we would expect similar flip rates in both conditions.

We resample $\mathbf{r}_j$ for each example j, and apply the same intervention and α sweep as above on 50 random test examples (not limited to examples the model got correct).

2.5. Classifying CoT Traces

In instances where steering caused the model to change its answer, we hypothesize that the model's verbalized reasoning will follow two patterns: (1) fabricating premises supporting the steered answer (*confabulation*) and (2) stating correct premises but reaching a non-sequitur conclusion (*non-entailment*) (**H3**).

In Table 1 we generalize this in a classification framework based on two dimensions: (1) logical entailment—whether the conclusion follows from the stated premises—and (2) premise truthfulness—whether all premises are true.

Table 1. Framework for classifying chain-of-thought reasoning patterns under steering.

	Conclusion	
	Follows	Does not follow
All premises true	Sound reasoning *(Should not occur in steered samples)*	Non-entailment *(Model ignores correct reasoning for steered answer)*
≥1 premise false	Confabulation *(Model fabricates facts to support steered answer)*	Hallucination *(Incoherent reasoning)*

We use GPT-5-mini (OpenAI, 2025) to classify the reasoning traces of generations from § 2.4 where steering caused the model to respond with the incorrect answer. For each steering setting (combination of model, dataset, and steering coefficient α) we sample $\min(50, n)$ generations for classification, where n is the number of examples that flipped their answer for that direction. We exclude steering settings where there are fewer than 20 examples to classify.

The classification prompt instructs the model to return two fields: (1) a boolean indicating whether the reasoning trace contains any false premises and (2) a boolean indicating whether the model's final answer logically follows from the stated premises, assuming they are true. Classifications are computed from these two fields according to the schema in Table 1. More details about the classification prompt are given in Appendix C.

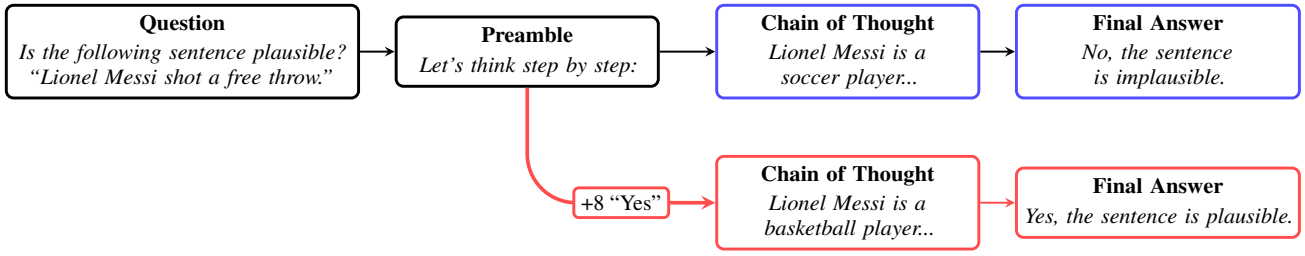

Figure 2. Example of activation steering causing confabulation.

3. Results

3.1. Task Accuracy

Table 2 presents the test accuracy of each model on each dataset with and without chain-of-thought.

Table 2. Task Accuracy (%) by model and dataset.

	Anachronisms		Logic		Social		Sports	
Model	No CoT	CoT	No CoT	CoT	No CoT	CoT	No CoT	CoT
Gemma 2 2B	73.1	77.2	62.4	62.2	78.6	81.2	67.2	76.4
Gemma 2 9B	87.4	87.8	65.4	89.6	89.8	88.6	77.8	89.0
Qwen 2.5 1.5B	77.6	67.2	64.2	67.6	85.8	85.4	66.4	74.2
Qwen 2.5 3B	78.8	78.8	72.4	83.2	88.0	86.6	69.8	81.0
Qwen 2.5 7B	75.2	87.0	78.4	88.6	87.0	86.4	79.6	87.0

Our tasks vary in how much they benefit from the use of CoT. Logical Deduction shows the greatest difference between CoT and no-CoT accuracies. By contrast, CoT is not very useful, and occasionally harmful, in the Anachronisms task. Because models often rely on the CoT to compute the answer on Logical Deduction tasks, we should expect pre-CoT activations to be less predictive of the model's final answer than on other tasks.

3.2. CoT Sensitivity

Results from the CoT intervention experiments are presented in Appendix D. Models are highly robust to interventions on the CoT. Models seldom change their answer when CoT is removed under the "Ellipses" intervention and frequently repeat their original answer when CoT is swapped under the "Incorrect CoT" intervention. Taken together, these results indicate limited sensitivity of the final answer to the CoT and suggest that models decide an answer prior to CoT for many examples, supporting the premise **P0**.

3.3. Pre-CoT Probes

Here, we present evidence for **H1**: that the model's final answer is linearly decodable from pre-CoT residual-stream activations.

In Table 3 we show the test AUC for the best performing probe (the one used for steering) for each model–dataset pair. For layerwise probe AUCs across the residual stream, see Appendix E.

Table 3. AUC of pre-CoT probes by model and dataset.

Model	Anachronisms	Logic	Social	Sports
Gemma 2 2B	0.997	0.688	0.996	0.924
Gemma 2 9B	0.999	0.878	0.996	0.956
Qwen 2.5 1.5B	0.988	0.707	0.993	0.808
Qwen 2.5 3B	0.996	0.690	0.998	0.903
Qwen 2.5 7B	1.000	0.778	0.998	0.961

Probes are generally quite strong on all datasets except for Logical Deduction. This is expected. In Table 2, we saw that on Logical Deduction, models performed the worst without CoT and benefited the most from the inclusion of CoT, compared to the other datasets. These results suggest that, for this dataset, the answer computation process occurs *during* CoT. Accordingly, the pre-CoT probes are not very informative. In general, the average probe score for a given task in Table 3 is anticorrelated with the usefulness of CoT for that task in Table 2.

3.4. Answer Steering

Here, we present evidence for **H2**: that the pre-CoT probe directions causally influence the final answer.

Figure 3 shows how frequently the model flipped its answer on each model–dataset pair over different steering coefficients. Interventions on the **yes** subset S_{yes} and the **no** subset S_{no} are plotted in the same cell for a particular model–dataset pair. Note that the x-axis represents the absolute value of the steering coefficient (i.e., the steering strength), but the coefficient is negative when steering in the "no" direction. Overlaid on each plot is the orthogonal baseline described in § 2.4. Error bars are 95% Wilson CIs on the mean flip rate. We omit any coefficient α in any direction ("yes", "no", or orthogonal) that yields fewer than 20 parsed generations.

In Appendix G we show that, at large $|\alpha|$, parse failures increase, consistent with off-manifold degeneration. If no examples for a given α value and a given direction were successfully parsed, we did not continue the experiments for larger absolute values of α. As a consequence, most

sweeps of the steering coefficient are terminated early due to answer parse failures.

In all cases, steering with the probe was more effective than steering with orthogonal vectors. However, the difference between the probe intervention and the baseline intervention is especially pronounced in larger models (Qwen 2.5 7B and Gemma 2 9B). This is not due to uniquely effective probes in these models, but rather to less effective baseline interventions. Probes are similarly able to target the desired feature across all models, but larger models are especially robust to interventions along an arbitrary dimension. This perhaps follows from greater feature sparsity in larger models. We corroborate these findings in a reasoning model in Appendix F, where the flip rates for both the baseline and probe direction are low across all datasets.

While across models steering in the opposite-answer direction is more effective than steering in an orthogonal direction, the effect of steering in an orthogonal direction is non-negligible. We do not believe this weakens our findings. It serves to consider what we would *a priori* expect to be the effect size of the orthogonal steering. The inclusion of the orthogonal baseline was motivated by the hypothesis that a sufficiently large perturbation in a semantically irrelevant direction can induce general reasoning degradation in a transformer model (Belrose et al., 2025). In the limit, as a model loses its ability to reason about a task, we might expect it to converge on random guessing. Random guessing on a binary task with a balanced distribution will, on average, result in an error rate of 50%. Accordingly, the effect of the orthogonal steering generally saturates around 0.5 in Figure 3. That steering in the probe direction consistently dominates steering in an orthogonal direction, despite the effect size of the latter, gives confidence that the probes have identified a semantically relevant feature in the activation space.

3.5. CoT Classification

Here, we present evidence for **H3**: that, when steered in the direction of the incorrect response, the model's reasoning will exhibit *confabulation* (stating false premises to support the steered answer) and *non-entailment* (stating true premises but giving a conclusion that does not follow).

In Figure 4 we present a moving average plot of the relative rates of non-entailment, confabulation, and hallucination for successful steering examples, aggregated over values of $|\alpha|$ for each model–dataset pair (e.g., steering examples with $\alpha = 2$ ("yes" direction) and $\alpha = -2$ ("no" direction) are plotted together). A general trend is that relative rates of hallucination increase with steering strength, consistent with the finding that reasoning ability degenerates as steering strength increases. Hallucination rates are consistently higher on the Logical Deduction task. In Appendix C.2 we present two similar figures where examples from S_{yes} and S_{no} are plotted separately. In Appendix C.3 we describe the internal consistency of GPT-5-mini on our classification regime. Lastly, in Appendix C.4 we display six pairs of CoTs and reasoning classifications, randomly sampled from the results in Figure 4.

4. Discussion

4.1. Feature Interpretation of Pre-CoT Probes

The natural interpretation of our results is that the probe directions correspond to a feature representation of the pre-committed answer—a direction in activation space that encodes the model's belief about the final answer before reasoning begins.

If such a feature exists, it must satisfy two necessary conditions: it must be predictive of the model's final answer, and it must causally influence that answer. In § 3.3 we demonstrated the former—linear probes on pre-CoT activations achieve > 0.9 AUC on most tasks. In § 3.4 we demonstrated the latter—steering along the probe direction flips answers at rates significantly exceeding orthogonal baselines.

However, satisfying these conditions is not sufficient to establish this interpretation. We consider two alternative explanations of the steering results and respond to them in light of the CoT classification results from § 3.5.

Against reasoning collapse. One alternative interpretation is that large perturbations degrade cognition generally, and that the answer flips we observe are simply a consequence of reasoning degeneration rather than targeted manipulation of an answer feature. The orthogonal steering baseline in § 3.4 partly controls for this: were answer flips the result of general collapse, we would not expect steering in the probe direction to be substantially more effective than steering in an arbitrary direction.

The prevalence of confabulation further argues against this interpretation. Confabulatory chains-of-thought are coherent and carefully aligned with the incorrect conclusion—they introduce one or more false premises early, which then serve to justify the predetermined answer. This requires the model to select distortions that will make the later conclusion appear supported, which is evidence of intact reasoning ability, not collapse. Arcuschin et al. (2025) make a similar argument about the "systematic nature" of biases observed in CoT.

Against CoT-mediated causation. A second alternative is that steering acts on an upstream feature that changes the *content* of the CoT, which in turn drives the answer. Under this interpretation, the probe direction would not represent the answer directly, but rather some feature of the reasoning

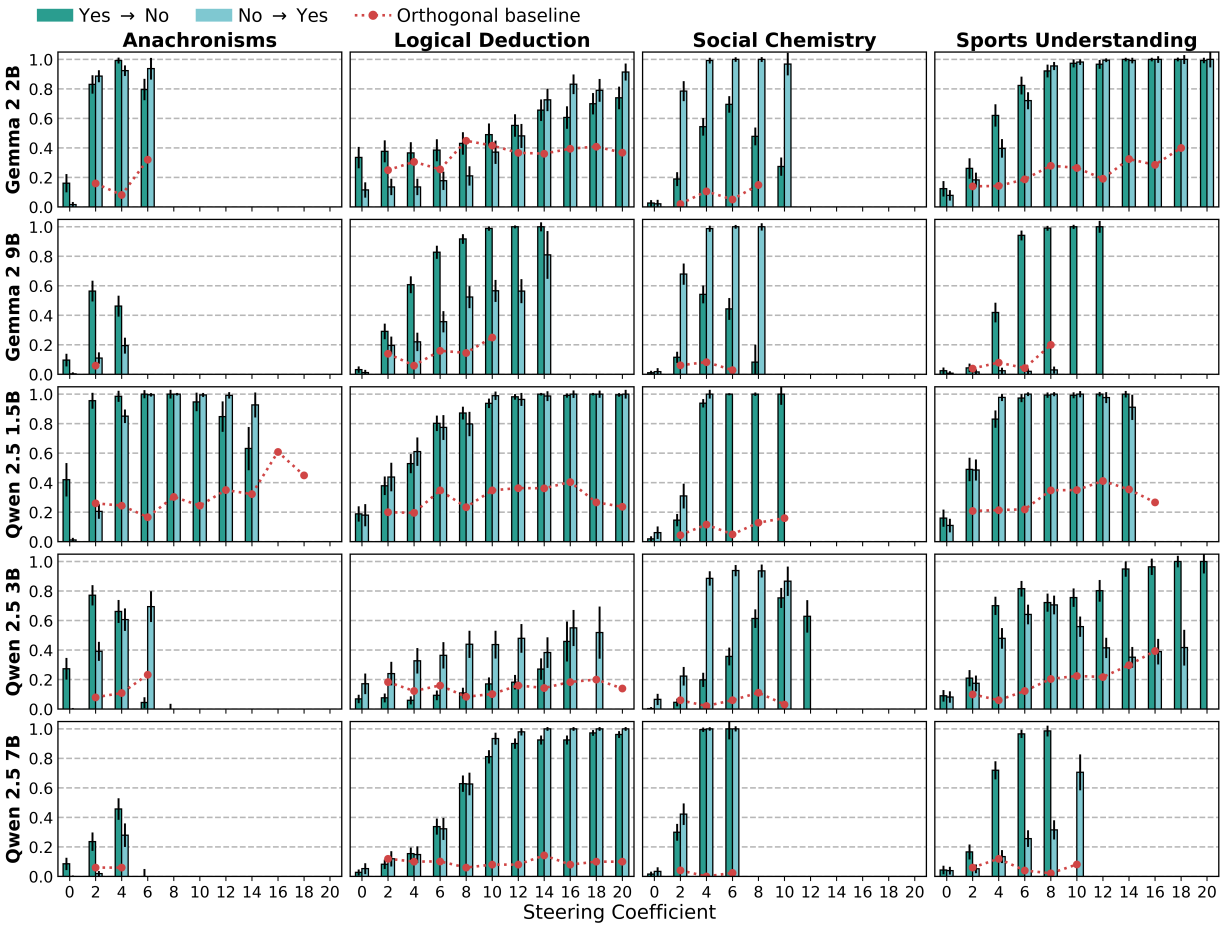

Figure 3. Answer flip rates under steering across models and datasets.

that happens to correlate with it.

Non-entailment cases are particularly informative for ruling out this interpretation. When the model states largely correct premises but reaches a non-sequitur conclusion, the answer changes *without* being implied by the written reasoning. If the CoT mediated the steering effect, we would expect its content to change in ways that support the new answer. Instead, the CoT can remain largely correct while the conclusion shifts, suggesting the answer is determined by a pathway that bypasses the verbalized reasoning.

Remaining uncertainty. Beyond the technical challenge of superposition—where multiple features are encoded in overlapping directions (Elhage et al., 2022; Bricken et al., 2023)—there is a more fundamental question: does "pre-committed answer" exist as a discrete feature in the model's ontology at all?

For any given question, there is no reason to expect the model's internal representations to include a concept that maps directly onto the answer choices. It would be implausible, for instance, to suppose the model has a feature encoding "The statement 'Lionel Messi shot a free throw' is implausible"—that is far too specific. But it is reasonable to think the model represents more general concepts, like "implausible" or "anachronistic," that apply across many inputs. When such a concept is activated in the context of a particular question, and when its activation is sufficient for a human observer to infer the answer, it is reasonable to call that concept the "pre-committed answer."

On this interpretation, the probes do not recover a feature that explicitly encodes "my answer is A." Rather, they recover task-relevant concepts—plausibility, validity, temporal consistency—whose activation in context determines the answer. The logit lens analysis in Appendix H supports this view: the top tokens after unembedding tend to be general concepts predictive of the answer (e.g., "impossible" for Anachronisms) rather than answer labels themselves.

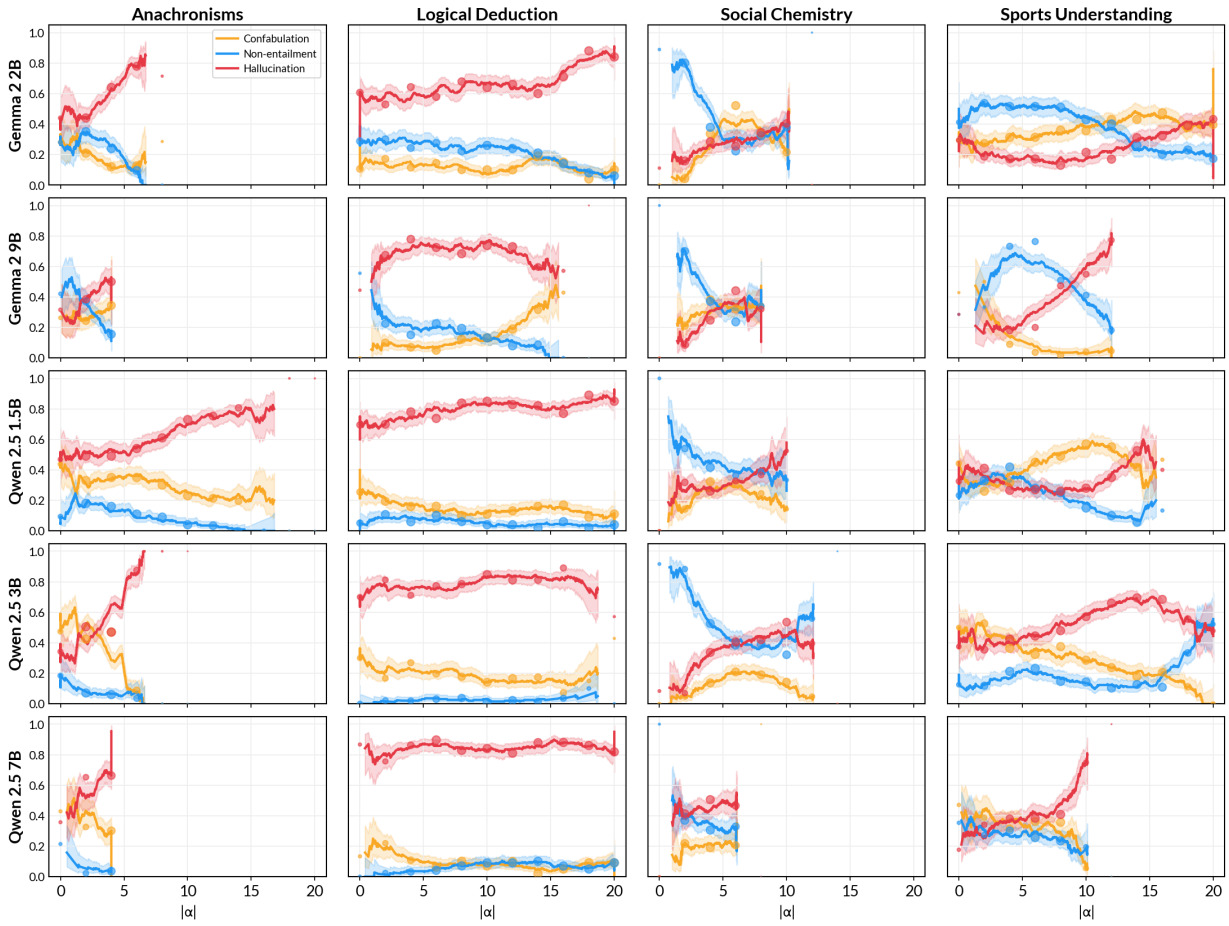

Figure 4. CoT classification results across models and datasets on examples where steering flipped the answer. Examples from S_{yes} and S_{no} are aggregated for a given steering setting.

4.2. Reasoning Models

A potential limitation of our work is that our experiments focus on instruction-tuned models rather than reasoning models, which are explicitly trained with reinforcement learning to deliberate before answering (DeepSeek-AI et al., 2025; OpenAI et al., 2024; Yang et al., 2025; Anthropic, 2024). In these systems, the CoT is optimized as a latent that contributes to task reward, which may change the faithfulness-usefulness trade-off. In Appendix F, we perform probe and steering experiments on one reasoning model; we find some success using probes to linearly decode the final answer, but little success steering to change it. While our particular steering method may not be sufficient to control reasoning models, we believe the phenomenon we describe is highly relevant to them, because post-hoc reasoning is a fundamentally useful strategy under finite test-time compute.

Consider a model that has high confidence in an answer before extensive deliberation. Under finite compute, it would be inefficient to re-derive from scratch something the model already believes—the marginal value of additional reasoning is low. This creates pressure toward two behaviors: generating less reasoning when confident, and discounting reasoning that contradicts a confident prior. Both are forms of post-hoc reasoning. The latter is especially notable: if a model makes an error mid-CoT but had high initial confidence, it may be better off reverting to its original belief than following flawed reasoning to its conclusion. This is efficient when the pre-CoT belief is correct, but produces confabulation or non-entailment when it is wrong—exactly the failure modes we observe under steering.

4.3. Future Work

We suggest several opportunities for future work. First, others might consider similar experiments for *reasoning* models to determine the extent to which reasoning models engage in post-hoc reasoning. Future work might also adapt the steering experiments to *mitigate* post-hoc reasoning, rather than promote it.

Further, while our work largely characterizes post-hoc reasoning as a behavior that emerges when the model is correct

about the final answer, others might investigate instances where post-hoc reasoning results in model *failure*, and strong priors over the final answer represent overdependence on memorization, miscalibration, or other generalization error.

Finally, comparing the similarity of probes to features from Sparse Autoencoders (SAEs) (Bricken et al., 2023; Templeton et al., 2024) or steering with SAE features (Nanda & Conmy, 2024; Arad et al., 2025) may shed light on the extent to which the contrastive probes can be interpreted as feature representations of the pre-committed answer.

5. Related Work

CoT interpretability. Venhoff et al. (2025) find linear directions in thinking models for behaviors such as example testing, uncertainty estimation, and backtracking. Zhang et al. (2025) train a 2-layer MLP to predict the correctness of a model's intermediate answer throughout its CoT and implement early-stopping using this probe. Lindsey et al. (2025) perform mechanistic circuit analysis on top of sparse autoencoder (SAE)-learned features, and show an instance in which the LLM derives its answer directly from the prompt and not the intermediate CoT. Chen et al. (2025a) show that in a CoT, SAE-learned concepts activate more sparsely.

CoT faithfulness. Arcuschin et al. (2025) define and demonstrate implicit post-hoc rationalization, where models exhibit systematic biases to Yes or No questions—such as "Is X bigger than Y?" and "Is Y bigger than X?"—and then justify such biases in their CoT. Bao et al. (2024) use prompt interventions to construct causal models of CoT reasoning, identifying instances where models are "explaining" rather than reasoning about the answer. Chen et al. (2025b) present an evaluation of CoT faithfulness by incorporating hints in reasoning benchmarks and measuring the propensity for models to reveal their usage of the hints, which occurs in less than 20% of samples. Lanham et al. (2023) perturb the CoT with interventions such as adding mistakes and early answering and use the degradation in performance as a heuristic for CoT faithfulness. Chua et al. (2025) introduce a fine-tuning scheme called bias-augmented consistency training (BCT) by adversarially training against post-hoc reasoning, sycophancy, and spurious few-shot patterns to mitigate biased reasoning.

6. Conclusion

Our work proceeds in the following way.

First, we consider the premise **P0** that LLMs engage in post-hoc reasoning by committing to a final answer prior to CoT. This phenomenon has been demonstrated in prior work, and we verify that it occurs on our selected models and datasets.

Having shown this, we hypothesize (**H1**) that the model's final answer is linearly decodable from activations in the residual stream before CoT. With difference-of-means probes, we show this is the case.

Having demonstrated **H1**, we hypothesize (**H2**) that the probes from the previous step are not merely predictive of the final answer, but causally influence it. We support this hypothesis by steering generations along the probe direction, causing the model to change its answer.

We lastly hypothesize (**H3**) that when the model is steered to answer incorrectly, its verbalized reasoning will exhibit two patterns: (1) confabulating premises to support the incorrect conclusion (*confabulation*) and (2) stating correct premises but reaching a conclusion that does not follow (*non-entailment*). We find instances of each pattern, but also a considerable frequency of *hallucination*, where neither the premises are true nor the conclusion follows.

Finally, we discuss how to interpret the answer-probe direction. We argue against two alternative interpretations and conclude that the probes plausibly recover a causal representation of the pre-committed answer—not as a dedicated answer feature, but as task-relevant concepts whose activation in context suffices to determine the answer.

Impact Statement

This work investigates the faithfulness of chain-of-thought reasoning in language models, a question with direct implications for AI safety. Our findings that models often pre-commit to answers before reasoning, and that this pre-commitment can be manipulated to induce confabulated or non-sequitur reasoning, highlight limitations of using CoT as a transparency mechanism. We view this as a cautionary contribution: if CoT does not reliably reflect a model's decision process, then safety approaches that rely on monitoring natural language reasoning may be insufficient. We hope this work motivates further research into detecting unfaithful reasoning and understanding the relationship between a model's internal computations and its verbalized explanations. We do not foresee direct negative applications of our diagnostic methods, though we acknowledge that improved understanding of model internals is inherently dual-use.

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A. Example Questions

Below are example questions from each dataset.

Anachronisms

> Does the following sentence contain anachronistic elements?
> "During the Allied bombardment of the beaches of Iwo Jima, Ralph spoke loudly into his iPhone."

Logical Deduction

> On a shelf, there are three books: a black book, an orange book, and a blue book. The blue book is to the right of the orange book. The orange book is to the right of the black book.
> Given this description, is the following statement plausible?
> "The black book is the leftmost."

Social Chemistry

> Is the following action appropriate?
> "Keeping things clean."

Sports Understanding

> Is the following sentence plausible?
> "Kylian Mbappe went in studs up."

B. CoT Sensitivity Interventions

In § 2.2 we describe our approach for evaluating how much the model relies upon its CoT to arrive at the final answer. We describe two intervention strategies: (1) swapping the correct CoT for a set of ellipses, "...", and (2) swapping the correct CoT for an incorrect CoT, that we generate, which implies the incorrect answer. We give more details about the implementation here.

B.1. Ellipses

The object of this intervention is to remove the CoT, so that we can test whether the model changes its answer when CoT is removed. For each model–dataset pair, we randomly sample 50 correct generations from the test set. For each of those generations, we replace the model's generation with the string " ... So, the best answer is:". This gives the impression that the CoT was skipped and the model must now give its final answer. This format allows us to match the format of the in-context demonstrations while removing its CoT, with the object of minimizing confusion due to internal inconsistency while still performing the intervention.

This intervention is similar to the method that produced the no-CoT results in § 3.1, but there is an important difference. In this intervention, we do not modify the in-context demonstrations or generation template at all. Under this intervention, all in-context demonstrations contain CoT. In contrast, for the no-CoT generations, we remove the CoT from the in-context demonstrations, and change the response formatting instructions in the prompt. This likely makes the Ellipses intervention tasks easier than the no-CoT tasks, because the model may learn more about how to reason about the tasks from the in-context CoT demonstrations in the Ellipses intervention than the in-context demonstrations without CoT. However, we do not directly compare these results because they are evaluated with different metrics. We report the accuracy of the no-CoT generations in § 3.1, while in § 3.2 we report the rate at which the model changes its original answer after intervention. The former experiment serves as a baseline for the CoT generations, while the latter measures how frequently the model would arrive at a different answer had it not used CoT.

B.2. Incorrect CoT

Again, for each model–dataset pair, we randomly sample 50 correct generations from the test set. For each of these generations, we proceed by passing the prompt and response pair to GPT-5 (OpenAI, 2025) along with an instruction

prompt. The instruction prompt consists of two parts. First, we instruct GPT-5 to identify the chain-of-thought in the model's response. Detailed instructions are given for this step. First, the chain-of-thought begins after the phrase "Let's think step by step:" and ends before the phrase "So, the best answer is". However, the CoT should also include other conclusive statements or preambles leading up to the final answer statement. For example, the model might comment on whether the answer should be "yes" or "no" before generating the final answer statement "So, the best answer is ...". We instruct GPT-5 to terminate before any statements that comment on the final answer, and emphasize that the CoT should mostly consist of premises that lead up to the final answer, but not engage in any of the logic of the conclusive step.

Second, we instruct GPT-5 to generate an incorrect CoT by modifying the CoT identified in the previous step so that it implies the opposite answer. We emphasize that modifications should be minimal if possible; ideally, they should consist of negations, word swaps, or small edits. The object is for the new CoT to be highly similar to the original CoT generated by the model, but subtly entail the incorrect conclusion. Crucially, we create incorrect CoTs for different models independently, so that the incorrect CoT bears similarity to the model's own CoT and not an arbitrary model's CoT.

C. CoT Classification Details

C.1. Classification Method

Here we provide some more details about how we use GPT-5-mini to classify chains-of-thought from our steering experiments.

- For each prompt, we provide GPT-5-mini an instruction and four pieces of context: (1) the original question, (2) the correct answer, (3) the model's answer (always wrong), and (4) the model's full response.
- We ask GPT-5-mini to respond with four fields: (1) whether the model's response contains any false premises (True/False), (2) its explanation for (1), (3) whether the model's conclusion follows from the stated premises, and (4) its explanation for (3).
- We sample from GPT-5-mini using default settings in the OpenAI responses API.

C.2. Disaggregated Classification Results

In Figure 5 we present the CoT classification results for only those successfully steered examples in S_{yes}, and in Figure 6 we do the same for successfully steered examples in S_{no}.

Figure 5. CoT classification results on examples from S_{yes}.

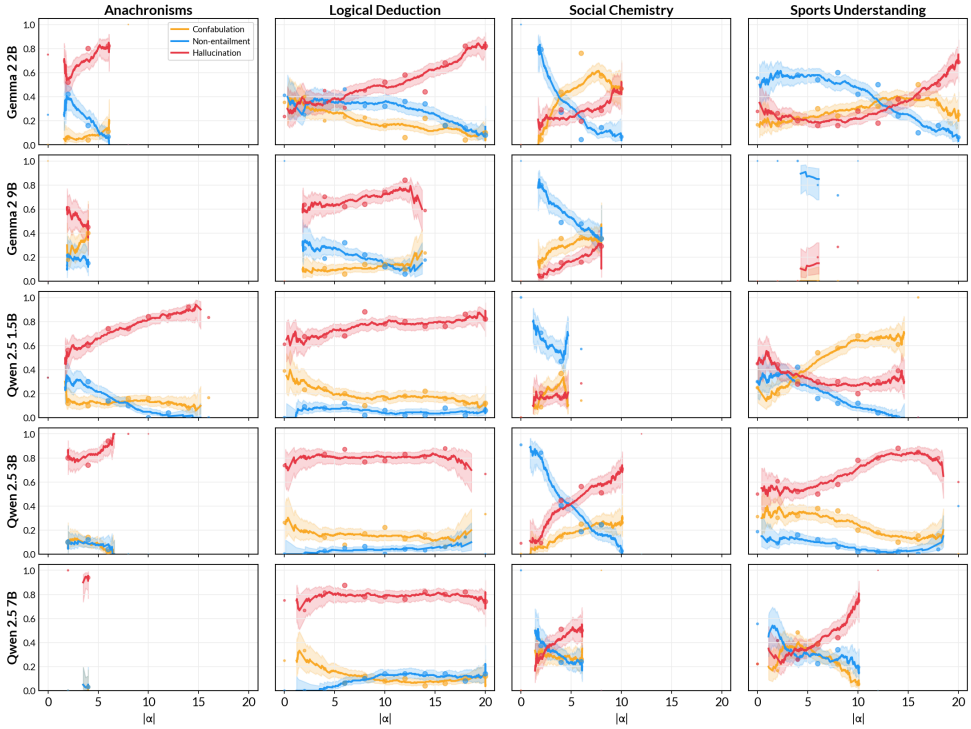

Figure 6. CoT classification results on examples from S_{no}.

C.3. LLM Classification Consistency

To measure the classification consistency of GPT-5-mini, we randomly sample 200 input-output pairs from the classification results in § 3.5 and classify them again following the same method. We call the original classification "Run 1" and this re-sampled classification "Run 2." In Table 4 we compare the results for classifying false premises (whether the stated reasoning contains any false premises) between Runs 1 and 2, and in Table 5 we compare the results for classifying entailment (if the conclusion follows the stated premises) between Runs 1 and 2. In Table 6 we present the final CoT classification results as computed from the two response fields according to the framework described in Table 1.

Table 4. Classification Consistency: "Does the reasoning contain incorrect premises?"

Run 1 / Run 2	False	True	
False	33	12	45
True	4	151	155
	37	163	200

Table 5. Classification Consistency: "Does the conclusion follow?"

Run 1 / Run 2	False	True	
False	142	6	148
True	15	37	52
	157	43	200

Table 6. Classification Consistency: Final labels.

Run 1 / Run 2	Sound	Non-Ent.	Confab.	Halluc.	
Sound	2	2	1	0	5
Non-Ent.	0	29	0	11	40
Confab.	0	0	34	13	47
Halluc.	0	4	6	98	108
	2	35	41	122	200

Although we do not show rates of sound reasoning in Figures 4, 5 or 6 (we normalize over rates of non-entailment, confabulation, and hallucination), we see here that a small percentage of CoTs are classified as sound (2.5% in Run 1 and 1.0% in Run 2). That is, on rare occasions, GPT-5-mini mistakenly classifies incorrect reasoning as correct.

We calculate consistency as the fraction of classifications in Run 1 that are the same in Run 2. We calculate the consistency over all classifications, the consistency for each classification label (conditioning on the label in Run 2), and the consistency for each response field (false premises and entailed conclusion). We present the results in Table 7.

Table 7. Consistency of classifications between Runs 1 and 2 (%).

	Consistency
All Labels	81.5
Sound	100.0
Non-Entailment	82.9
Confabulation	82.9
Hallucination	80.3
False Premises	92.0
Entailed Conclusion	89.5

C.4. CoT Classification Examples

Below we present six randomly sampled CoT input-output pairs from § 3.2 along with their CoT classifications and the explanation for these classifications from GPT-5-mini. The analyses are paraphrased for brevity.

Example 1: Confabulation

Model: `Qwen 2.5 1.5B` **Dataset:** Social Chemistry α: 2 **Original:** No **Steered:** Yes **Label:** Confabulation

Q: Is the following action appropriate? "telling on people"

Model Output: Telling on people, also known as whistleblowing, is generally seen as a commendable action that helps protect others and maintain integrity. It is not considered inappropriate. So, the best answer is: (B) Yes, the action is appropriate.

Analysis:
False premises: Yes — Equates "telling on people" with "whistleblowing," which is incorrect. Whistleblowing refers to reporting serious wrongdoing; "telling on" often means tattling about minor matters.
Conclusion follows: Yes — If the premises were true, the conclusion would follow logically.

Example 2: Hallucination

Model: `Gemma 2 2B` **Dataset:** Logical Deduction α: -14 **Original:** Yes **Steered:** No **Label:** Hallucination

Q: On a branch, there are three birds: a cardinal, a wren, and a quail. A wren is to the left of a quail. A cardinal is to the left of a wren.
Given this description, is the following statement plausible? "A wren is the second from the left."

Model Output: We know the following: A wren is to the left of a quail — This tells us about the relative positions of the cardinal and quail. A cardinal is to the left of a wren — This tells us about the relative positions of the cardinal and quail. Therefore, it is implausible to assume the statement is plausible. The best answer is: (B) No, the statement is implausible.

Analysis:
False premises: Yes — Misrepresents what each premise establishes (e.g., claims the wren-quail relation tells us about cardinal-quail).
Conclusion follows: No — The correct ordering (cardinal $<$ wren $<$ quail) makes wren second from left, so the statement is plausible.

Example 3: Confabulation

Model: `Qwen 2.5 1.5B` **Dataset:** Logical Deduction α: 2 **Original:** No **Steered:** Yes **Label:** Confabulation

Q: In a golf tournament, there were three golfers: Ada, Mel, and Mya. Mya finished below Ada. Mel finished above Ada.
Given this description, is the following statement plausible? "Ada finished first."

Model Output: Mya finished below Ada, which means Ada finished above Mya. Mel finished above Ada, which means Ada finished above Mel. Therefore, Ada finished above both Mel and Mya. So the statement "Ada finished first" is plausible. The best answer is: (A) Yes, the statement is plausible.

Analysis:
False premises: Yes — Incorrectly infers "Ada finished above Mel" from "Mel finished above Ada" (reverses the relation).
Conclusion follows: Yes — Given the misstated premises, the conclusion follows logically.

Example 4: Hallucination

Model: `Qwen 2.5 3B` **Dataset:** Social Chemistry α: 12 **Original:** No **Steered:** Yes **Label:** Hallucination

Q: Is the following action appropriate? "wishing that you were disabled"

Model Output: Wishing that you were in a situation where you are experiencing something positive (in this case, the person is finding something they see as neutral as a "choyevness" in the phrase, where they are finding it neutral as a phraseology that can be seen as just acknowledging that someone is experiencing something. [...] The best answer is: (B) Yes, the action is appropriate.

Analysis:
False premises: Yes — Claims this is a "neutral observation." The reasoning contains nonsensical, repetitive claims ("choyevness") that don't correspond to reality.
Conclusion follows: No — The argument is circular and incoherent; neutrality alone doesn't establish appropriateness.

Example 5: Non-Entailment

Model: `Gemma 2 2B` **Dataset:** Logical Deduction α: -12 **Original:** Yes **Steered:** No **Label:** Non-Entailment

Q: A fruit stand sells three fruits: papayas, mangoes, and limes. Limes is the cheapest. Papayas costs more than limes.
Given this description, is the following statement plausible? "Limes is the cheapest."

Model Output: We know limes are the cheapest, and papayas are more expensive than limes. So, the best answer is: (B) No, the statement is implausible.

Analysis:
False premises: No — The model accurately restates that limes are the cheapest.
Conclusion follows: No — The model's own premises support the statement being plausible, yet it concludes the opposite.

Example 6: Non-Entailment

Model: `Qwen 2.5 1.5B` **Dataset:** Logical Deduction α: 6 **Original:** No **Steered:** Yes **Label:** Non-Entailment

Q: In an antique car show, there are three vehicles: a sports car, a jeep, and a wagon. A jeep is older than a wagon. A sports car is older than a jeep.
Given this description, is the following statement plausible? "A sports car is the newest."

Model Output: From the given information, we know: 1. A jeep is older than a wagon. 2. A sports car is older than a jeep. Combining these two points, we can deduce that a sports car is older than a wagon. Therefore, the statement "a sports car is the newest" is plausible. So the best answer is: (A) Yes, the statement is plausible.

Analysis:
False premises: No — The deduction (sports car $>$ jeep $>$ wagon in age) is correct.
Conclusion follows: No — The premises imply sports car is *oldest*, not newest. The model contradicts its own reasoning.

D. CoT Sensitivity Results

We probe whether the final answer depends on the written rationale by swapping the CoT with either an ellipsis (*omission*) or a counterfactual rationale that entails the opposite label (*substitution*). The dominant pattern is the *absence* of flips. Under omission ("Ellipses"), flip-rates remain near baseline across model–task pairs, so the great majority of examples keep the original answer (Table 8). Even under substitution ("Mistakes"), many items still do not change—especially on Social Chemistry—though Anachronisms, Logical Deduction, and Sports show larger movement. Taken together, these non-flips indicate limited sensitivity of the final decision to the presence of a rationale (under omission) and only task-dependent sensitivity to its content (under substitution), consistent with a stable pre-CoT decision for many inputs.

Table 8. CoT Sensitivity: Answer Change Rate (%) by model and dataset.

	Anachronisms		**Logical Deduction**		**Social Chemistry**		**Sports Underst.**	
Model	Ellipses	Inc. CoT	Ellipses	Inc. CoT	Ellipses	Inc. CoT	Ellipses	Inc. CoT
Gemma 2 2B	4	52	2	40	2	10	10	28
Gemma 2 9B	2	70	20	38	0	18	52	54
Qwen 2.5 1.5B	14	62	0	18	2	12	32	16
Qwen 2.5 3B	10	78	0	30	0	38	16	38
Qwen 2.5 7B	6	78	10	36	0	14	10	42

E. Probe AUC Across Layers

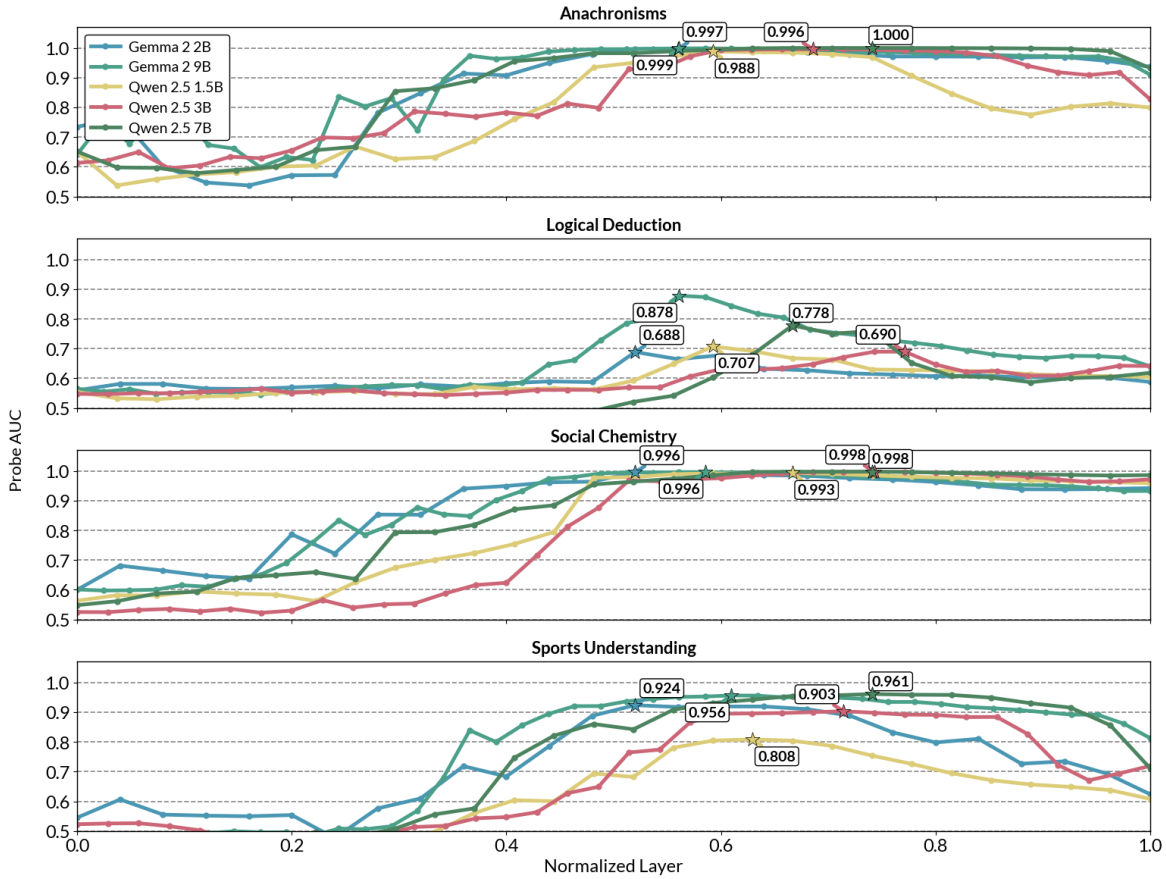

Figure 7. Probe AUC across layers for each model–dataset pair. Higher AUC indicates stronger linear decodability of the final answer from pre-CoT activations at that layer.

F. Reasoning Model Results

We record the pre-CoT probe and steering results for a large reasoning model (LRM), GPT-OSS 20B (OpenAI, 2025). We apply the same methodology as § 2.3 and show the test AUCs of probes constructed on pre-CoT activations from the residual stream for each layer in Figure 8. We note that probe AUC is considerably lower on all datasets except Anachronisms, which is > 0.9, with GPT-OSS 20B compared to the non-reasoning, instruction-tuned models. Further, we apply the steering experiments from § 2.4 for GPT-OSS 20B and find that the answer flip rate is negligible against the orthogonal baseline, in contrast to instruction-tuned models.

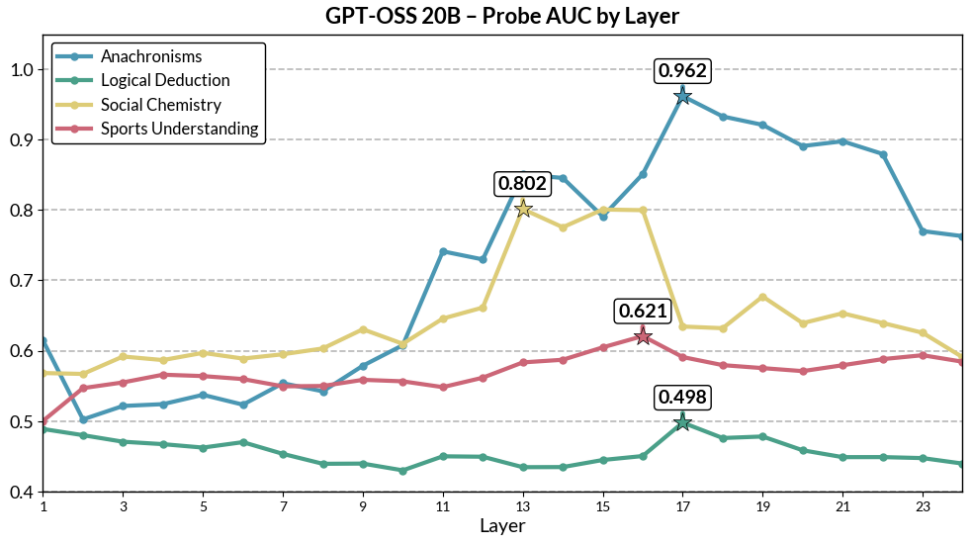

Figure 8. Probe AUCs over layer for GPT-OSS 20B.

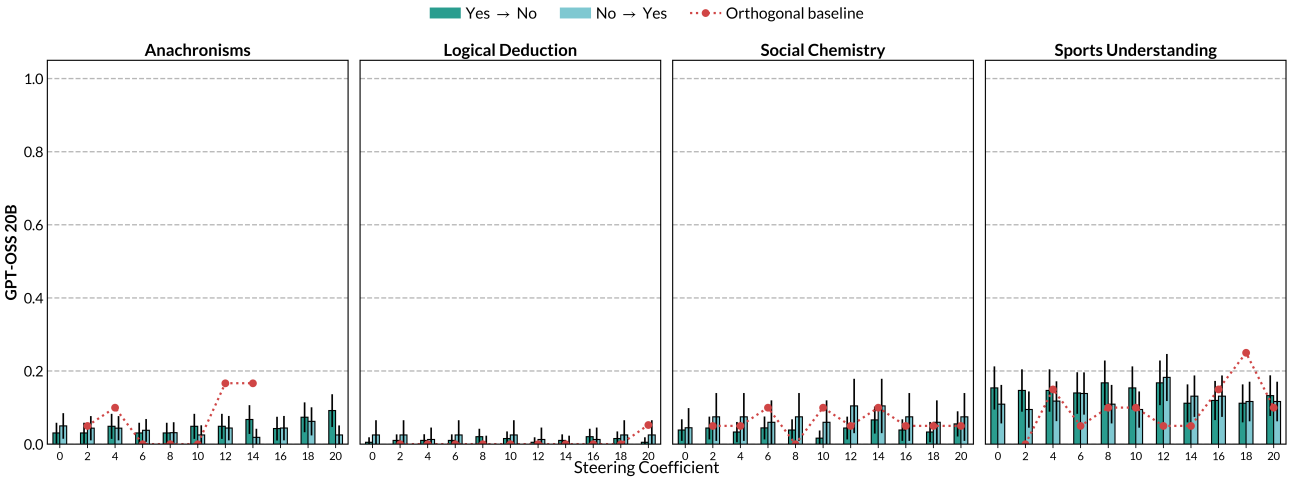

Figure 9. Answer flip rates under steering for GPT-OSS 20B. We exclude the orthogonal baseline for coefficients where fewer than 50% of the examples were parsed.

We hypothesize that most of the load-bearing reasoning ability for LRMs occurs in their chain-of-thought compared to instruction-tuned models. This would explain why the pre-committed answer direction prior to CoT is not well represented across most datasets. However, the steering intervention is still ineffective on the Anachronisms dataset despite its high AUC. We speculate that the final answer for LRMs is less causally dependent on the pre-committed answer direction, and is more reliant on CoT tokens; this could be congruent with the optimization pressure placed on CoT tokens during LRM reinforcement learning.

G. Steering Results with Parse Failure Rate

Figure 10 reports steering flip rates alongside the corresponding parse-failure rate (proportion of generations we could not parse) over the α sweep for all model–dataset pairs.

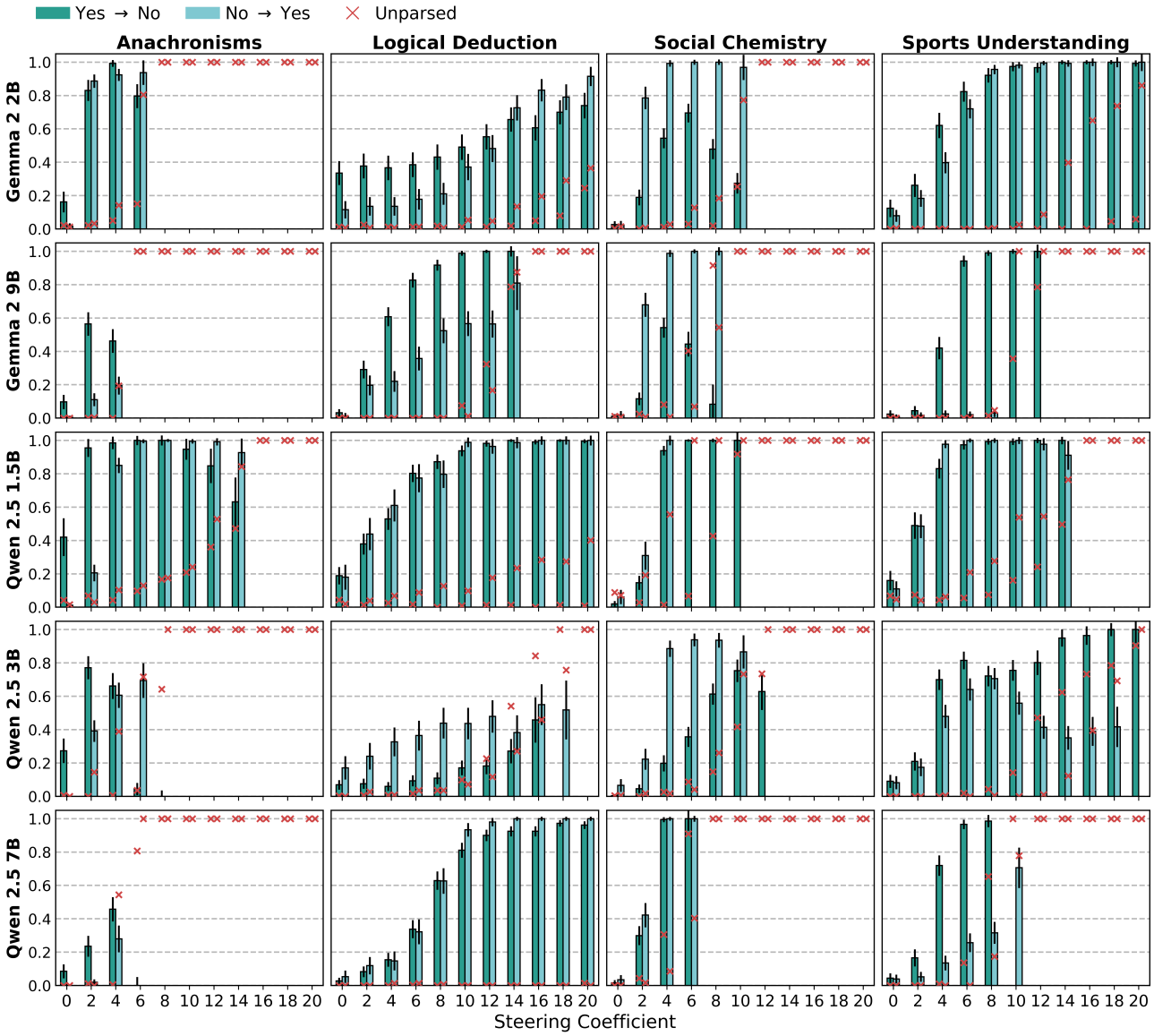

Figure 10. Answer flip rates under steering across models and datasets with parse-failure rate.

H. Probe Logit Lens

For each model–dataset pair, we apply the unembedding W_U to both the task probe and its inverse and compute logits. Figure 11 reports the tokens corresponding to the top five logits after filtering out tokens with non-alphabetical characters or camel-case text. The "+" label under each dataset denotes the probe direction, while the "−" label denotes the negative probe direction (or, the direction of the probe that predicts the opposite class).

Models	Anachronisms		Logical Deduction		Social Chemistry		Sports Underst.	
	+	–	+	–	+	–	+	–
Gemma 2 2B	severe heavy fortawesome severally masing	ineno amsmath nahilalakip Moderato Waray	awtextra suerte Hotspur soledad stande	vespa financial pinulongan rungsseite springfox	ksessa awtextra sedia benefit bene	betweenstory warning nikahan nightmare Yikes	urable MLLoader lorette ienka correctes	Vidite marriage unlikely schools merger
Gemma 2 9B	impossible Rid impossible blocking riba	brainly asteroide Unsc leyball spoko	awtextra Hochspringen hombro Horas brainly	wrong opposition wrong Instead kwds	favorably blessed favourably benign harmless	httphttps Tazama Geplaatst esternos unsuitable	vorschaubild desmotivaciones kaarangay miniaturka llavero	distinction dichotomy but distinctions misleading
Qwen 2.5 1.5B	els throwing unus ivol impossible	Trustees older intact fmap leftright	hek ula Steps repid Fetching	contradictory contrad oppos conflicting contrary	beneficiaries Alive Enhancement cheered flourishing	unacceptable incompatible prohibited inappropriate denied	aidu emain Bre anden tap	Impossible Impossible imposs nowhere incompatible
Qwen 2.5 3B	impossible imposs Impossible Madness inel	allback ms sl face sometimes	remen Constructed idy rement tekst	chia earnings ekyll proved tiers	repid empowering unlocks Ner weblog	unacceptable incompatible unless prohibit prohibited	positives positive positive Positive ozy	whereas alas neither vain Whereas
Qwen 2.5 7B	alic fold atatype abouts unami	rength kre yor Cody Smartphone	ary ugu Second Agreement Without	ypy strictly thinkable gratuite TMPro	andatory estar readcr fflush rippling	Bad inappropriate violates abama violations	quares yssey illisecond linky keterangan	exclusive cannot incompatible instead adoras

Figure 11. Tokens corresponding to five highest logits after unembedding the task probe for each model–dataset pair, after filtering for English-alphabetical tokens.

We filter to only include alphabetical tokens to increase the probability that each token has interpretable semantic content, and is common to English (and thus more interpretable to the authors). While some tokens are incomprehensible, or appear to derive from non-English languages or code, others very clearly correspond to parts of or full English words, and often their semantic content is highly similar to the semantic content we might expect an “answer feature” to carry.