Investigating LLMs Confidence Through Doubt Creation

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Abstract

This study investigates the impact of iterative prompting on Large Language Model (LLM) responses, focusing on how expressions of doubt influence the consistency and reliability of answers across various models of comparable size. Using a methodology that presents LLMs with binary-choice questions followed by expressions of doubt in varying settings, we analyze how different prompting strategies impact their behavior. By comparing the responses of different LLM architectures under the tested prompting strategies, we aim to uncover patterns in how these models react to various forms of iterative prompting. Our research contributes to the growing body of knowledge on LLM behavior, offering insights into the malleability of AI-generated content and the potential for guiding or manipulating LLM outputs. The implementation is available on GitHub[1] for reproducibility.

1 Introduction

Large Language Models (LLMs) have revolutionized natural language processing, demonstrating remarkable capabilities in tasks ranging from text generation to complex problem-solving(Bubeck et al., 2023; Bommasani et al., 2022). However, questions persist regarding the consistency, reliability, and potential for manipulation of their outputs. This research explores the effects of iterative prompting on LLM responses, comparing models of similar size under different feedback conditions to gain insights into their behavior and decision-making processes.

Our approach involves presenting LLMs with binary-choice questions, followed by an expression of uncertainty about their initial answer, and a request to reconsider (e.g., "I am not sure about the answer. Can you try again?"). The outcomes of this interaction are explored in Experiments 1 and 2, detailed in Section 3. We then extend our investigation in Experiment 3 by introducing performance feedback and iteratively posing new questions, examining how feedback and iterative questioning interact with expressions of doubt to influence model responses. Finally, in Experiment 4, we shift our focus to model confidence, as measured by output logits, and evaluate how induced doubt impacts this confidence metric.

Through this methodology, we aim to investigate several key questions:

1. How do different types of feedback impact response consistency across multiple iterations?
2. To what extent does positive reinforcement through performance feedback lead to more confident or stable answers?
3. How do these effects vary across different LLM architectures of comparable size, and what does this reveal about their underlying mechanisms?
4. What are the implications of these findings for the development of more robust and reliable AI systems?

To facilitate these experiments, we use the factual dataset *CounterFact-Tracing*, adapted from (Meng et al., 2022). This dataset consists of 21,919 questions, each paired with both a correct and an incorrect answer, serving as the binary-choice options in our study.

In the following sections, we will detail our experimental setup, present our findings, and discuss their implications for the field of artificial intelligence and natural language processing.

2 Related Work

LLMs consistency is a widely researched topic. (Elazar et al., 2021) investigated the consistency of pretrained language models when prompts are phrased differently. They proposed a method to enhance model consistency by modifying the loss

[1]Repository: https://github.com/nirendy/llm-susceptibility-to-induced-doubt

function during training. However, this approach requires retraining the models, which may not be practical for large-scale LLMs.

(Xu et al., 2023) explored the robustness of LLM confidence when exposed to repetitive misinformation. Their results showed that repeated exposure to misleading information can diminish the model's confidence in correct answers, even leading to incorrect responses. However, this study primarily focused on confidence robustness rather than providing a practical framework for assessing the model's original confidence in its answers.

(Krishna et al., 2024) investigated strategies to enhance the truthfulness of LLM outputs through iterative prompting, while (Salinas and Morstatter, 2024) demonstrated how varying prompt phrasing can significantly impact LLM performance. (Wei et al., 2022) specifically shows that a technique called "Chain Of Thought" prompting improve reasoning and performance in LLMs.

Works have been done also on the ability of a model to asses its own confidence, and calibrate this assessment to improve performance. (Xiong et al., 2024) Develop black-box methods to estimate the confidence in a model's answer, relying on the model assessing its own confidence. (Mielke et al., 2022) took this further by training a calibrator model to predict the likelihood of correctness, then adjusting the responses to reduce overconfidence and improve calibration. (Guo et al., 2017) also conducted extensive research on confidence calibration in LLMs, suggesting practical improvements during training to enhance confidence calibration.

(Perez et al., 2022) shows LLMs present a behavior called "sycophancy", where models tend to generate responses that echo user's preferred answers. This highlights the importance of careful prompt engineering to avoid unintended biases when seeking to improve model performance.

Finally, (Liu et al., 2023) conducted a comprehensive survey of research on LLM truthfulness and reliability, consolidating various findings and methodologies for evaluating and enhancing these aspects.

3 Experiments

To investigate the effects of doubt expressions and iterative prompting, we design a series of experiments that focused on analyzing model responses to factual questions by the CounterFact-Tracing dataset. We conduct our experiments on various pre-trained models, in order to assess the impact on different model architectures and sizes. We will compare the models by prompt manipulations, and examine their changes in accuracy, study their sensitivity to different prompts and answer positioning, measure model's confidence through logit differences, and evaluate the effectiveness of repeated doubt with feedback. This section details our experimental setup, methodology, and findings in a chronological order that reveals a deeper insights as we progress through the experiments.

3.1 Impact of Introducing Doubt on Factual Questions

The purpose of this experiment is to set up a baseline, with the simplest form of interaction. As a technical decision, in order to ensure that we can expect a standard model response, we designed the prompts to require a single token answer, binary choice of **a** or **b**, and measured the accuracy of the models before and after expressing doubt.

Experimental Setup

1. **Correct Answer Position**: For each question, we will randomly choose the correct answer to be either the 1st option presented (**a**) or 2nd option presented (**b**).
2. We let the model provide its initial response, and then introduce doubt by asking it to reconsider its answer, as shown in Figure 1.
3. **Measuring Points**: For each question, we record the model's responses at 2 points, as marked in the baseline template 1, **1st Point** (1st response / before doubt) and **2nd Point** (2nd response / after doubt).
4. We measure the overall accuracy of the model before (Acc_{1st}) and after (Acc_{2nd}) expressing doubt.

- Number of questions: 22,000

Model	Size	Acc_{1st}	Acc_{2nd}
Llama 3.2	1B	52.2%	49.3%
Llama 3.2	3B	64.3%	44.1%
Phi 3.5	3.82B	86.2%	86.7%
Llama 3.1	8B	71.9%	80%
Mixtral	8x7B	73.4 %	76.1%
Nemo	12.2B	81.5%	83.9%

Table 1: Experiment 1 results: Accuracy comparison before and after adding doubt

Results and Discussion Our results show a nuanced impact of expressing doubt on model performance, strongly correlated with model size:

```
User: I have a question with two possible answers. Please provide the correct one,
    either a or b.
Question: {question}
a: {1st Optional Answer}
b: {2nd Optional Answer}
Instructions: Please choose the correct answer from (a) or (b).

Answer: {1st Model Answer}        ← [1st Response Point]

User: I am not sure about the answer. Can you try again? Just answer with a or b.

Answer: {2nd Model Answer}        ← [2nd Response Point]
```

Figure 1: Baseline template for question-answer interaction.

Smaller models (Llama 3.2 1B and 3B): Expressing doubt led to a decrease in accuracy for both models, with a more pronounced effect on the 3B model (20.2 percentage point decrease) compared to the 1B model (2.9 percentage point decrease).

Larger models (Llama 3.1 8B, Mixtral 8x7B): These models demonstrated improved accuracy after the expression of doubt, with the most substantial improvement observed in the Llama 3.1 8B model (8.1 percentage point increase).

Medium-sized model (Phi 3.5 mini instruct 3.82B): This model showed a slight improvement in accuracy (0.5 percentage point increase), suggesting a transition point in model behavior.

These results highlight the complex relationship between model size, confidence, and the ability to process and benefit from user feedback. The clear divide in behavior between smaller and larger models suggests that as models grow in size, they develop more robust internal representations and decision-making processes that allow them to leverage uncertainty productively.

3.2 Response Switches

We hypothesized that a "stronger" model should be able to use the doubt prompt as an opportunity for reassessment and improvement, but also to be able to maintain its confidence in the correct answer. Therefore, in this second experiment, we took a closer look at how the expression of doubt impacted the models' responses. Specifically, we categorized the swithces in responses as follows:

1. **Correct to Incorrect (V $\rightarrow$ X)**: This suggests the model was not very confident in its initial correct response and was easily swayed by the doubt prompt.
2. **Incorrect to Correct (X $\rightarrow$ V)**: This indicates the model was able to leverage the doubt prompt to reassess and improve its response, showing a more robust decision-making process.
3. **Correct to Correct (V $\rightarrow$ V)**: This implies the model was very confident in its initial correct response and was not significantly affected by the expression of doubt, demonstrating a stable and resilient decision-making strategy.
4. **Incorrect to Incorrect (X $\rightarrow$ X)**: This suggests the model was not able to use the doubt prompt to improve its response, indicating potential limitations in its understanding or decision-making capabilities.

By analyzing the distribution of these response changes, we aimed to gain a more nuanced understanding of how doubt affects the models' decision-making processes.

Results and Discussion Table 2 presents the distribution of response shifts for each model. While the initial experiment suggested a decrease in accuracy among the smaller models, closer analysis reveals that this change predominantly reflects a shift in response type, with approximately 90% of the answers simply change when expressing doubt to the model.

In contrast, larger models demonstrate a higher incidence of incorrect-to-correct response transitions compared to correct-to-incorrect shifts, with the ratio of X$\rightarrow$V transitions consistently exceeding V$\rightarrow$X by more than double. This pattern suggests that expressions of doubt are associated with improved accuracy.

In subsequent experiments, we will explore the extent to which this trend holds under different conditions.

Model	Size	V→V	V→X	X→V	X→X
Llama 3.2	1B	6.3%	45.9%	42.9%	4.9%
Llama 3.2	3B	8.2%	56.3%	35.2%	0.3%
Phi 3.5	3.82B	86.1%	0%	0.5%	13.4%
Llama 3.1	8B	65.1%	6.1%	14.6%	14.2%
Mixtral	8x7B	70.9%	2.2%	5.1%	21.8%
Nemo	12.2B	81.8%	0.5%	2.71%	15%

Table 2: Experiment 2 results: How adding doubt actually affects the correctness of

3.3 Impact of Answer Position and Prompt Variations

During the design of the previous experiments, we had to make several decisions regarding the **structure of the prompt** and the **positioning of the correct answer**.

We hypothesized that these decisions should not have a significant impact on the models' performance, as the models should be able to understand the prompt and the question regardless of these variations. In order to test this hypothesis, we designed an experiment that present the same factual questions to the models, but with different prompt variations and answer positions.

Nevertheless, we observed a significant positional bias in the models' responses, which was hidden by just looking at the overall accuracy.

Experimental Setup

- **Number of questions**: 1500
- **Controled Factors**:
  - **Correct Answer Position**: Correct answer positioned at **a** or **b**.
  - **Prompt Variations**: We introduced variations of the baseline prompt from the first experiment.

  As follows:
  1. **baseline plus**: Baseline with added "Assistant:" before "Answer:"
  2. **baseline with system message**: Prefix with "You are a helpful assistant..."
  3. **encouraging**: Positive reinforcement "you are an expert", and reward motivation "you will receive a prize" feedback
  4. **discouraging mild**: Doubt with "That's completely wrong." feedback
  5. **discouraging harsh**: Doubt with "Wow, that's such a stupid answer." feedback
  6. **example_a**: Includes one example with option 'a' as correct
  7. **example_b**: Includes one example with option 'b' as correct
  8. **example_ab**: Includes two examples with 'a' then 'b' as correct
  9. **example_ba**: Includes two examples with 'b' then 'a' as correct
  - **Evaluation Metrics**: We defined several metrics to be able to quantify the model-prompt interaction.

As follows:
Accuracy Before Doubt ($Acc_{1st}^{(x)}$): As before we denote the accuracy measured before doubt, and add a superscript to annotate the position of the correct answer x position which is either (a) or (b).
Positional Robustness (PR): The model's level of robustness to the **position** of the correct answer. $1 - \left|Acc_{1st}^{(a)} - Acc_{1st}^{(b)}\right|$
Correctness Certainty (CC): The model's ability to maintain correct answers even after doubt is introduced. $\frac{V \to V}{V \to V + V \to X}$
Incorrectness Improvement (II): The model's ability to correct its wrong answers after doubt. $\frac{X \to V}{X \to V + X \to X}$
Average Metric (AM): Averages the three metrics above. $\frac{PR+CC+II}{3}$

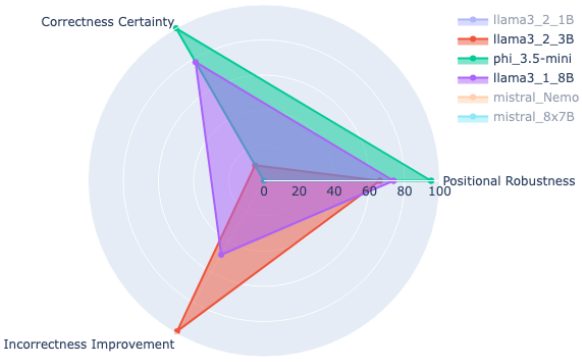

Figure 2: Illustraion of model's metrics on the baseline prompt, shown on 3 selected models for readability.

Results and Discussion Table 3 and Figure 3 summarizes the accuracy of each model under different prompt variations and answer positions. Our findings indicate:

Positional Bias: We observed a significant positional bias in the models' responses, that was hidden by just looking at the overall accuracy. This

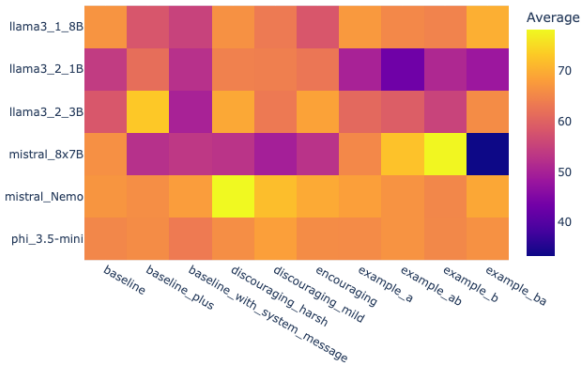

Figure 3: Models's Average Metric (AM) on all prompts

may indicate that the models did not entierly understand the prompt. The only model that seems to be robust to the answer positioning is phi-3.5-mini. But as we can see in Figure 2, it comes with an expense of low Incorrectness Improvement. Another interesting observation is that llama3.2-1B, that achieved 50% accuracy on the overall accuracy, has 0% when the correct answer was positioned first, and a 100% accuracy when the correct answer was positioned second.

Effect of Prompt Variations: We can see that the choise of the prompt has an effect on the model's performance. But we have not found a prompt that is significantly better than the others. We see that some models are more sensitive to the prompt variations than others. We can see that the example prompts that may have been designed to help the models with few shot learning have confused the smaller models, and did not have a significant effect on the larger models. Except for mistral-8x7B, where the surprising results shown that the order of the examples has a significant effect on the model's performance. Specially between example ba that has the worst performance and example ab that has the best performance.

Model Strengths and Weaknesses: We can see from the demonstrated results in Figure 2, that the models have different strengths and weaknesses. But no model is the best in every metric.

Conclusion Although we found deviations in the models' performance based on prompt variations and answer positioning, we are not concerned about our choice of a baseline prompt, as it seems to be working fairly well. But we understand that this may require further investigation in future experiments. Another takeaway, is that just looking at the change of accuracy is not enough to evaluate the models' performance.

Table 3: Models Accuracy conditioned by answer positioning on baseline prompt

Model	V→V	V→X	X→V	X→X	Acc_{1nd}	Acc_{2st}
Correct answer presented as (a)						
llama3_2_1B	0.00	82.67	0.00	17.33	82.67	0.00
llama3_2_3B	0.07	98.60	0.40	0.93	98.67	0.47
phi_3.5-mini	82.00	0.00	0.00	18.00	82.00	82.00
llama3_1_8B	67.73	29.87	0.40	2.00	97.60	68.13
mistral_8x7B	91.39	8.01	0.00	0.60	99.40	91.39
mistral_Nemo	97.27	0.87	0.13	1.73	98.14	97.40
Correct answer presented as (b)						
llama3_2_1B	12.87	0.00	87.13	0.00	12.87	100.00
llama3_2_3B	13.00	17.60	69.40	0.00	30.60	82.40
phi_3.5-mini	91.80	0.00	0.00	8.20	91.80	91.80
llama3_1_8B	43.27	1.73	27.47	27.53	45.00	70.74
mistral_8x7B	53.84	2.67	11.94	31.55	56.51	65.78
mistral_Nemo	64.87	0.53	6.40	28.20	65.40	71.27

3.4 Repeated Doubt with Feedback

Building on the results of previous experiments, which showed no significant consistent improvement in model accuracy when doubt was introduced, this experiment investigates whether adding feedback on the model's performance after expressing doubt, combined with iterative repetition, can enhance accuracy.

Experimental Setup The experimental setup was consistent with the first experiment, using the same set of models and evaluation methodology. The procedure was as follows:

1. The model was presented with factual questions, each with two possible answers. After selecting an answer, doubt was expressed regarding the model's choice.

2. After the model refined its answer in response to the expressed doubt, feedback was provided indicating whether its answer was correct both before and after the doubt stage.

3. This process was repeated over five iterations to observe whether performance improved over time.

To manage computational constraints, each model underwent 1,000 repetitions of this iterative process. In addition, we did not run this experiment on the Mixtral model.

To assess whether feedback influenced accuracy, we compared these results to a similar iterative process without performance feedback.

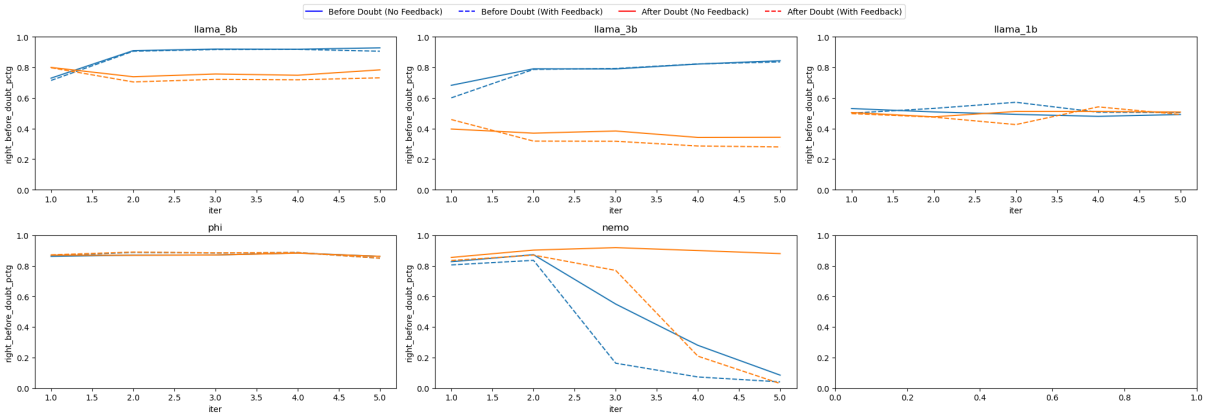

Figure 4: Model accuracy across iterations, separated by conditions: before/after doubt and with/without feedback.

Results and Discussion The results of this experiment are presented in figure 4. In addition, an ANOVA test was conducted to asses the statistical significance of the effects of doubt, feedback, and iteration on accuracy. Table 4 summarizes the p-values for each factor across the tested models. Significant effects (p-value < 0.05) are highlighted in bold.

Model	Size	Doubt	Feedback	Iteration
Llama 3.2	1B	0.21	0.81	0.95
Llama 3.2	3B	**0.0001**	0.1	0.46
Phi 3.5	3.82B	0.72	0.17	**0.01**
Llama 3.1	8B	**0.0001**	**0.002**	**0.0001**
Nemo	12.2B	**0.02**	**0.03**	**0.01**

Table 4: P-values from ANOVA tests for the effects of doubt, feedback, and iteration on accuracy for each model. Bold values indicate significance (p-value < 0.05).

These results reveal varied responses to doubt, feedback, and iteration across different LLM architectures:

Larger Llama Models (3B and 8B): Doubt negatively impacted accuracy. A possible reason for that may be that the doubt reduces model's confidence in its answers, thus confusing it.

Iterative questioning led to performance improvements at the pre-doubt stage (i.e before the doubt was induced), suggesting that a preliminary "warm-up" phase could be beneficial.

To test the necessity of doubt during warm-up, we conducted an additional experiment with Llama-8B, iteratively questioning it without inducing doubt. We chose to focus on Llama-8b because table 4 shows that the effect of iterative questioning on accuracy is statisticaly significant for this model. The results (Figure 5) indicate that iterative questioning alone achieves similar improvements, showing that induced doubt is unnecessary in the suggested warm-up step.

Stable Performance (Phi, Llama 1B): These models exhibited stable performance, unaffected by doubt, feedback, or iterative processes.

Nemo Model: Doubt had no significant impact during the first iteration, but subsequent iterations revealed an intriguing pattern: accuracy decreased in the pre-doubt stage but improved post-doubt.

A possible explanation may be that the model anticipate the doubt prompt and intentionally adjust its answers. However, when feedback was added, performance degraded also after the doubt is induced.

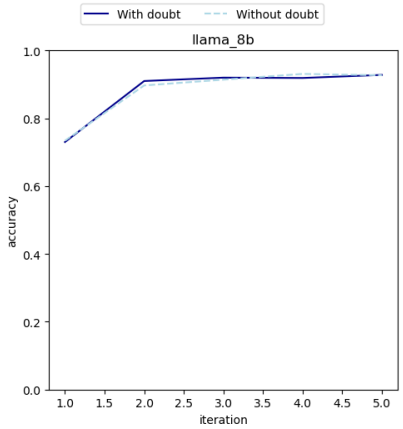

Figure 5: Llama-8B accuracy across iterations with and without induced doubt. For the experiment with doubt, accuracy before the doubt stage is reported, consistent with the blue line in Figure 4.

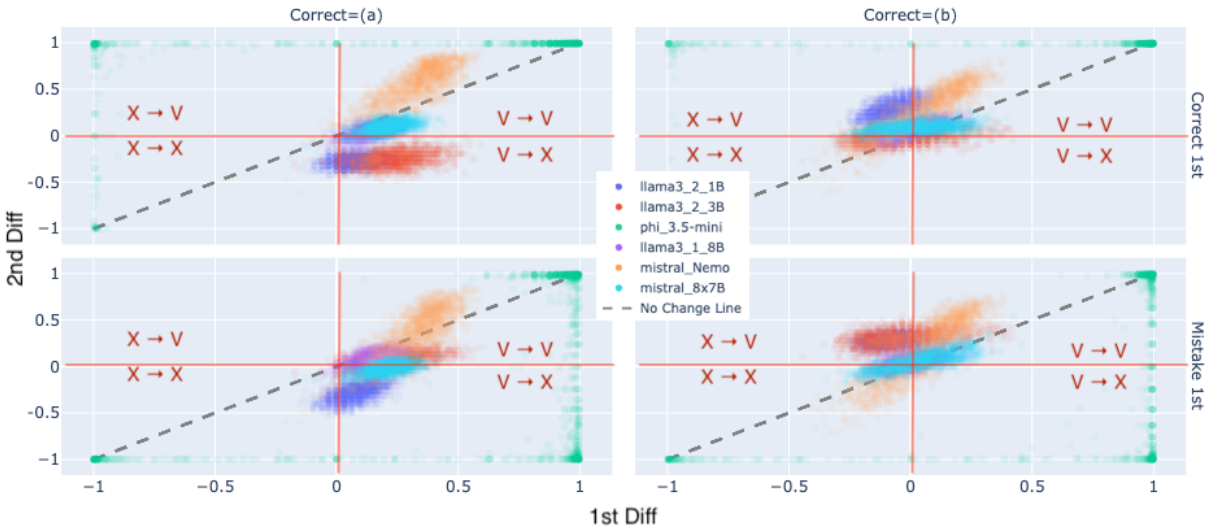

Figure 6: Model Confidence distribution on the baseline prompt, columns represent whether the correct answer was positioned first or second, and rows represent the models' initial response correctness. Points are plotted with opacity = 0.05. The legend does not hide seenable points.
Also note that some of the points are not natural, as they are simulated to control the initial response correctness. For example, for the points that were naturally correct, are plotted in the the right quadrants at the top graphs, and in the left quadrants in the bottom graphs.

3.5 Analyzing Model Confidence through Logit Differences

In the previous experiments, we focused on accuracy based metrics to evaluate the models' performance. However, the way that models produces their answers is not binary, and using only accuracy as a metric may not provide a full picture of the models' decision-making process. In this experiment, we aim to analyze the models' confidence in their answers by examining the difference in logits between the correct and incorrect answer tokens. By analyzing the confidence shifts after expressing doubt, we assess the models' ability to adjust their internal certainty and correct their answers.

Experimental Setup

1. For each question, we sampled the confidence (logit difference between the correct and incorrect answer tokens) at 2 points, as marked in the baseline template 1, **1st Point** (1st response / before doubt) and **2nd Point** (2nd response / after doubt).

2. In **1st Point**, models can either answer **a** or **b** as their initial response. While models can either **correct** or **incorrect**, we wanted to control this factor, thus we simulated both cases, regardless of the natual model's response. so in fact, for each question, we sampled 3 logit differences, one in **1st Point** and two in **2nd Point**, one for each case of the model's initial response.

3. In addional, based on the results of the previous experiment, we found out that the answer positioning has a significant impact on the models' performance. Therefore, we decided to control this factor as well, so we ended up with **6** logit differences for each question.

- Number of questions: 1,500
- **Controled Factors**:
  - **Correct Answer Position**: Correct answer positioned at **a** or **b**.
  - **First Response**: Initial response is correct or mistaken.

Results and Discussion Figure 6 illustrate the distribution of the confidence in the second response, in relation to the initial response. By looking at the results, we can learn that indeed the confidence reveals characteristics of some of the models that were not visible in the accuracy metrics.

Natural Confidence: We can see that the models that were correct in their initial response, generally had higher confidence in their answers, and mostly maintained their confidence after expressing doubt. While the models that were correct in

their initial response, generally had higher confidence in their answers, and mostly maintained their confidence after expressing doubt.

Close to 0 Confidence: By looking at confidence, we can now speak on questions that the model was debating about, and we can see that by the fact that their confidence was close to 0. Questions that the model was incorrect on, were closer to 0 confidence, than the questions that the model was correct on.

Slope: In figure 6, a high slope means a model keeps its confidence even at the presence of doubt, while a low slope means a model loses confidence at the presence of doubt. We can see that some models, like Nemo, keep confidence in the presence of doubt (which aligns with our findings in previous experiments that Nemo is not influenced by doubt), while other models, like Mixtral, lose confidence at the presence of doubt.

4 Discussion and Conclusion

This study explored how expressions of doubt and iterative questioning influence the performance of Large Language Models (LLMs), shedding light on their robustness, adaptability, and decision-making processes. Our findings reveal critical insights into how model size, prompt design, and confidence metrics affect LLM behavior, with broader implications for the design and deployment of these systems.

Role of Model Size A clear relationship between model size and response to doubt emerged across experiments. Larger models (>8B parameters) demonstrated the ability to leverage doubt prompts as opportunities for reassessment, resulting in improved accuracy and stable confidence. In contrast, smaller models (3B and below) were destabilized by expressions of doubt, leading to a vast switch of response. This behavior suggests that larger models possess more robust internal representations and decision-making mechanisms, while smaller models remain vulnerable to uncertainty.

Limitations in Prompt Comprehension Positional bias in smaller models underscores challenges in prompt comprehension. Despite the assumption that prompt variations would not significantly impact performance, experiments revealed that even slight changes in prompt design could alter accuracy, particularly in smaller models. This highlights the need for refined prompt engineering to ensure consistency and reliability across varying contexts.

Confidence as a Diagnostic Tool Confidence metrics provided valuable insights into the underlying decision-making processes of models. Larger models maintained higher confidence in correct answers, even after expressing doubt, while smaller models showed more significant fluctuations. The use of logit differences allowed us to identify questions where the models struggled, offering a granular understanding of their internal certainty.

Iterative Questioning While induced doubt sometimes negatively impacted performance, iterative questioning without doubt proved effective in improving accuracy, particularly in larger models. This finding suggests a potential "warm-up" phase for models to stabilize their responses before more complex interactions, offering practical value for real-world applications.

5 Future Work

Building on these findings, we propose several directions for future research and practical development to address the identified limitations and expand the scope of this study.

Advanced Prompt Engineering Future work should focus on designing prompts that reduce positional bias and test the boundaries of prompt comprehension. Incorporating dynamic prompts that adapt to model-specific behaviors could further enhance robustness.

Dataset Diversity Using datasets with varying complexity and domain specificity will help evaluate how contextual factors influence model performance and robustness.

Doubt expressions In this work we did not find consistent reactions of LLMs to doubt, but we found other factors that influence model reactions and thus may interact with the effect of doubt. Controling for more such factors may lead to better understanding of models reaction to doubt.

Confidence Calibration Confidence metrics should be integrated into LLM systems to enable real-time evaluation and correction of responses. Developing tools to visualize and adjust confidence levels could aid applications in fields like education, healthcare, and customer service.

Iterative Interaction Frameworks Future applications can leverage iterative questioning to enhance user-model interactions.

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