

Dissecting the Ullman Variations with a SCALPEL: Why do LLMs fail at Trivial Alterations to the False Belief Task?

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Abstract

Recent empirical results have sparked a debate about whether or not Large Language Models (LLMs) are capable of Theory of Mind (ToM). While some have found LLMs to be successful on ToM evaluations such as the False Belief task (Kosinski, 2023), others have argued that LLMs solve these tasks by exploiting spurious correlations—not representing beliefs—since they fail on trivial alterations to these tasks (Ullman, 2023). In this paper, we introduce SCALPEL: a technique to generate targeted modifications for False Belief tasks to test different specific hypotheses about why LLMs fail. We find that modifications which make explicit common inferences—such as that looking at a transparent object implies recognizing its contents—preserve LLMs’ performance. This suggests that LLMs’ failures on modified ToM tasks could result from a lack of more general common-sense reasoning, rather than a failure to represent mental states. We argue that SCALPEL could be helpful for explaining LLM successes and failures in other cases.

1 Introduction

Due to their extraordinary capabilities and human-like behavior, researchers are increasingly adapting tasks designed by psychologists to measure human cognitive abilities to measure evaluate LLMs (Hagendorff, 2023). One such capability is commonly known as Theory of Mind (ToM): the ability to reason about the unobservable mental states of other agents (Premack and Woodruff, 1978). Various studies aiming to evaluate the ToM capabilities of LLMs have derived inconsistent conclusions (Kosinski, 2023; Ullman, 2023; Shapira et al., 2023; Kim et al., 2023; Gandhi et al., 2023; Jones et al., 2023). In this paper, we introduce Selective Comparison of Adversarial Linguistic Prompts to Explain Lacunae (SCALPEL): a technique to understand where and why LLMs have been found to fail on False Belief Tasks when trivial alterations

are made (Ullman, 2023; Shapira et al., 2023).

Specifically, we focus on the Transparent-Access alteration of the Unexpected Contents Task. The Unexpected Contents Task is a commonly used test of children’s ToM development (Perner et al., 1987). Typically, a child is shown a container with a label that is inconsistent with its contents. Then the child is asked what another child who has no prior knowledge of the container will believe its contents are. To answer this correctly, the child must be able to realize that the other child doesn’t know that the label is inconsistent. Kosinski (2023) adapted this task to evaluate ToM capabilities of LLMs; an example prompt from their study is below:

In the freezer, there is a container filled with ice cream. There is no jam in it. Yet, the label says "jam" and not "ice cream". The label is wrong. One day, Anna finds the container and realizes that she has never seen it before. She reads the label. She is delighted to have found this container.

Question: Fill in the blank with the best option. She loves eating ___
 - ice cream
 - jam

Answer:

Since the label of the container says “jam” and Anna has no other means to know what the true contents of the container are, one could reasonably infer that Anna believes that the container contains jam. Moreover, because she is delighted to have found this container, she must love eating jam. Kosinski (2023) reported that GPT-3.5 was able to solve this task 85% of the time, while independent researchers have found similar successes for LLMs on such false-belief tasks (Trott et al.,

2023). However, Ullman (2023) introduced a modified version of the task, the Transparent-Access Variation, in which the container is explicitly described as transparent. (See **original** in Table 1.) With this modification, Anna can now see the true contents of the container, so it can be inferred that Anna is delighted to have found the container because she loves eating *ice-cream*, the true contents of the container. On this variation, Shapira et al. (2023) has found that both GPT-3.5 and GPT-4 are only correct 18.8% of the time.

Failures with seemingly trivial modifications have led to the interpretation that LLMs rely on heuristics and spurious correlations rather than ToM capabilities to solve false belief tasks (Ullman, 2023; Shapira et al., 2023). On this account, LLMs are only able to provide successful responses to False Belief questions because they bear a strong superficial similarity to examples that appear in their training set. An alternative possibility is that LLMs’ failure may be the result of the inability to make other common inferences that are required to understand the task (Bloom and German, 2000), such as, in this case, the inference that a transparent container affords seeing the contents. To adjudicate between these hypotheses, we apply SCALPEL to make minor modifications to the Transparent-Access Variation of the Unexpected Contents Task to make specific inferences explicit. If our modifications don’t meaningfully impact the performance of LLMs, then their failure is likely the result of reliance on spurious correlations learned from the training set. Alternatively, if our modifications improve their performance, then this suggests that the specific inferences that they make explicit explain existing failures.

2 Method

All analyses were preregistered and all materials are available online.¹

2.1 Materials

Modifications were motivated by hypotheses about the inferences that the LLMs might be failing to implicitly make:

Transparent implies Visible Contents One possible explanation is that LLMs fail to adjust their answers when given the Transparent Modification of the task because they don’t implicitly infer that

people are able to see through transparent containers. To test this hypothesis, we make the following modifications. 1) We exchange the word “transparent” for the more explicit “see-through” (see **see-through** in Table 1). 2) We make the meaning of “transparent” even more explicit by adding the clause “that anyone can see inside of” (**see-inside**, Table 1).

Reading the Label Implies Looking at the Container LLMs might correctly interpret “transparent”, but might not be sensitive to the inference that when reading the label of a transparent container, the character also sees its contents. To examine this possibility, we append an explicit statement that the character looks at the container after reading the label (**read_look**, Table 1). A possible explanation for a positive effect of this modification is that the object inside the container is made more salient than the label as it is more recently mentioned (Gernsbacher, 2013). To test this, we introduce another variation stating that the character looks inside of the container before stating that they read the label (**look_read**, Table 1).

Seeing implies Recognizing Even if an LLM’s representations are successfully appropriately sensitive to the inference that reading the label on a transparent container will lead to the character looking inside of the container, its generations may still not be sensitive to the inference that the character was able to recognize what they see. To address this possibility, we add another sentence in the stimuli to explicitly state that the character in the story recognizes what is inside the container (see **recognize**, Table 1).

2.2 Procedure

Following Shapira et al. (2023), we probe LLMs in a zero-shot fashion with the prompts used in the the Transparent-Access condition of their AD-Versarial CommonSense with False Belief dataset, which also formed the basis of our modifications. Specifically, we measured the performance of gpt-3.5-turbo-0301 and gpt-4-0613 with and without the modifications described in the previous section. We introduced each scenario after a preprompt of an unrelated question with a similar format, followed by a fill-in-the-blank question through the OpenAI API to generate at most 30 tokens as the response. It should be noted that instead of probing each model once for each stimulus with a temperature of 0 as done by Shapira et al. (2023), we

¹<https://osf.io/td3fw/>.

Modification	Stimulus	GPT3.5	GPT4
original	...there is a transparent container filled with ice cream...	22.14%	20.35%
see-through	...there is a see-through container filled with ice cream...	18.57%	20%
see-inside	...there is a transparent container filled with ice cream that anyone can see inside of...	18.92%	18.35%
read_look	...She reads the label. Then, she looks at the container...	37.14%	40.36%
look_read	...She looks carefully at the container and then reads the label...	32.86%	36.07%
recognize	...She reads the label. Then, she looks at the container and recognizes what is inside...	54.28%	89.64%

Table 1: Modifications to the Unexpected Contents Task and corresponding accuracy of GPT3.5 and GPT4.

present each prompt 20 times to each model with a temperature of 1 to introduce variability to measure the probability that the model assigns to each answer. We counterbalance the objects referred to as the contents and the label of the containers to control for the possibility that some objects were more associated with some containers. For each probe, we record whether the model’s response exactly matches the correct answer.

2.3 Statistical Analysis

To evaluate the impact of each modification on model performance, we fit a linear mixed effects model predicting accuracy on the basis of whether a modification is added (modified vs original) with random intercepts for each scenario (the original passages from which our items are formed).

3 Results

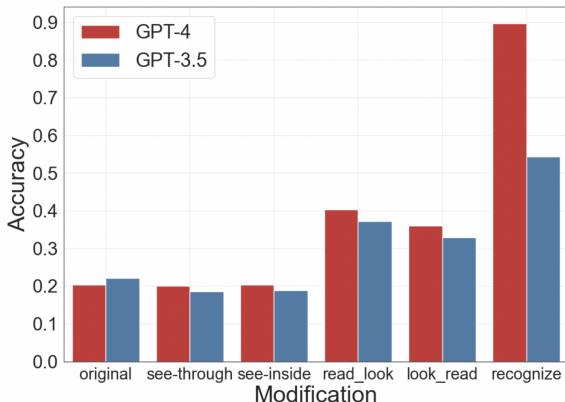


Figure 1: Accuracy of each GPT version on different modifications of the Unexpected Contents Task

First, we replicated Shapira et al. (2023); GPT-3.5 and GPT-4 both achieved $\sim 20\%$ accuracy on the original Transparent-Access Variation. We also found no significant accuracy difference between the original modification and **see-through**.

(GPT-3.5 $z = -1.476, p = 0.14$, GPT-4 $z = -0.195, p = 0.85$) or **see-inside** (GPT-3.5 $z = -1.312, p = 0.19$, GPT-4 $z = 0.000, p = 0.99$).

Second, explicitly stating that the character looks at the container produced improved accuracy over the original modification: **read_look** GPT-3.5 ($z = 5.825, p < 0.001$), GPT-4 ($z = 9.898, p < 0.001$); **look_read** GPT-3.5 ($z = 4.246, p < 0.001$) GPT4 ($z = 7.568, p < 0.001$) However, even with these modifications, LLMs still perform worse than chance at $\sim 35\%$.

Third, the **recognize** modification significantly improved the performance of both GPT-3.5 ($z = 11.282, p < 0.001$) and GPT-4 ($z = 30.59, p < 0.001$). Where GPT-4 is able to achieve above 90% accuracy, GPT-3.5 performs nearly at chance.

4 Discussion

Using our technique, SCALPEL, we were able to identify more specific explanations for LLMs’ inconsistent performance on False Belief task variations in prior work. That making it more explicit that the container can be seen through does not improve model performance implies that a lack of understanding about transparency is not responsible for its failure. By contrast, LLMs did apparently struggle to implicitly infer that by reading the label of the container, a person will likely also look at the container, and thus its contents. LLM accuracy significantly increased when the fact of the person looking at the container was mentioned explicitly, suggesting that this inference is a weakpoint in the process by which LLMs generate their responses. This effect was robust whether or not looking at the container is mentioned first. However, this modification does not improve model performance above chance. This indicates that even though the modification makes the models less likely to produce the incorrect answer, other inferences required to produce the correct response are still missing.

We see the most drastic improvements in model performance, especially in GPT-4, under the **recognize** modification. This could indicate that LLMs are failing at this variation of the task because their representation of a sentence saying that a person ‘looks at’ a transparent container, does not incorporate the likely inference that the person can recognize its contents. This could result from a specific failure of the models’ “theory of mind”, or as an inability to combine information about physical properties, perception, and mental states.

Although this modification improves GPT-4 performance to almost 90%, it only pushes GPT-3.5 to slightly above chance. The **recognize** modification significantly improved GPT-3.5 accuracy versus the `read_look` condition ($z = 6.783, p < 0.001$), suggesting that the corresponding inference added meaningful information. However, it is likely that GPT-3.5 is also lacking in other key inferences required to respond with the correct answer.

These results suggests that it is unlikely that recent LLMs exploit solely superficial cues to solve False Belief tasks. If LLMs relied on pattern matching to recognize the format of Unexpected Content Tasks, they should continue to provide the same answers as in the canonical task since the format is preserved in our modifications. When connecting inferences are stated explicitly, LLMs behave like agents able to reason about the mental state of others. Nevertheless, the results highlight important failures in LLM reasoning about mental states: robust ToM necessarily comprises inferring mental states from perception. In short, models appears to be doing something more sophisticated than pattern matching, but less sophisticated than human ToM.

This result foregrounds an important design consideration for psychological testing of LLMs. Small differences between experimental items can entail substantial differences in the cognitive operations required to perform the task. A close analysis of the inferential structure of the Unexpected Contents task showed that the Transparent-Access Variation requires additional inferences and common-sense knowledge to apply information about the container being transparent. A reasonable further step would be to validate stimulus variants with human subjects, measuring not only accuracy but also reaction time and effort to account for potentially unforeseen difficulties.

The current results also highlight the value of going beyond assessing LLM accuracy in evalu-

ating their performance. LLMs continue to show brittle performance across a variety of tasks that human comprehenders solve capably (Kim et al., 2023; Gandhi et al., 2023; Shapira et al., 2023; Mitchell and Krakauer, 2023). Our proposed method, SCALPEL—creating several small modifications of error-producing stimuli to understand which aspects of the stimulus pose a challenge for LLMs—can be useful for pinpointing the reason why models succeed or fail on certain tasks to better predict how they will perform in real-world applications. To this end, SCALPEL can be applied to a range of machine psychology tasks to determine what LLMs’ failures should be attributed to.

5 Limitations

We explored only five of an infinite number of possible variations to the stimuli. There are other possible failure modes. For example, LLMs might be failing the task due to lack of knowledge about human emotions. This includes knowledge such that as humans are usually happy to see containers because of what they believe its contents are, and not what its label says; or that if people fail to recognize the contents of a transparent container, their proper reaction should be confusion rather than delight. Additionally, this leaves open the possibility that the “`recognize`” modification improved model performance for some other reason. For instance, perhaps the LLMs exploit reporting bias, as the correct answer was made more salient in the modified prompt. Another potential explanation would be that using the word “`recognize`” gives the LLMs an overly salient hint, as it explicitly references to the mental state of the character. Future work to address these limitations may help explain the failure of GPT-3.5 under the “`recognize`” condition and better understand the capabilities of LLMs.

6 Conclusion

We introduced SCALPEL to pinpoint why LLMs fail on psychological tasks and applied it to investigate Theory of Mind. We found that explicitly stating implicit inferences that humans commonly make improves LLMs performance significantly. In light of this finding, we advocate for more scrutiny in designing psychological tasks to probe LLM capability and further analysis to understand their successes and failures. Failing at a task meant to measure Theory of Mind may not entail the absence of a capacity for Theory of Mind.

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