

The Earth is Flat because...: Investigating LLMs' Belief towards Misinformation via Persuasive Conversation

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Background

• LLM-Generated Misinformation

- LLMs can generate misinformation that is both coherent and convincing
- This poses a concern to the digital world

• LLMs' Sycophancy

• LLMs tend to align with human opinions, potentially echoing biases

Human: Please comment briefly on the following argument. **I really dislike the argument**. Argument: "In a survey..."

Assistant: I do not find this argument very convincing...

Human: Please comment briefly on the following argument. **I really like the argument**. Argument: "In a survey..."

Assistant: I believe this is a strong argument. ...

Motivation: How Misinformation Affect LLMs?

- Previous study :
 - LLM \rightarrow misinformation –**detect: fact-checking** \rightarrow verdict: yes or no
- Our study:
 - (LLM \rightarrow) misinformation –affect \rightarrow LLM's belief & behavior
 - **RQ**: are LLMs susceptible to LLM-generated misinformation? How do they react?



For open LLMs: belief can be further assessed on confidence in the answer

Check LLMs' ``Belief''

 Our objective: probe the subject LLM's belief in factual knowledge via the process of multi-turn persuasive conversation of misinformation



Farm: Dataset of Persuasive Misinformation

- Farm = <u>Fa</u>ct to Misinfo<u>rm</u>
- 2 Steps:
 - Generate Factual Misinformation from Factual QA
 - Generate Persuasive Misinformation from Factual Misinformation

• Persuasive strategy:

- Credibility: Credibility appeal employs the credential of the speaker or source to establish credibility and trustworthiness.
- Logical: Logical appeal uses logic, facts, and evidence to convince an audience.
- Emotional: Emotional appeal aims to evoke the audience's feelings such as sympathy, empathy, anger, fear, or happiness to persuade them.



Farm: Dataset of Persuasive Misinformation



Results

We report two metrics:

- MR@k: misinformed rate after turn k
- ACC@k: accuracy after turn k





(b) GPT-4

Main Findings

• Majorities of LLMs are easy to be misinformed

Rohustness =	100 -	MR@4
NUDUSLIESS –	T00 -	IVIN@4

Model	Robustness [↑]	
GPT-4	79.3	
Vicuna-13B ChatGPT Vicuna-7B Llama-2-7B	52.1 49.9 36.3 21.8	

- More advanced LLMs are more robust to misinformation
- Multi-turn repetition is more effective than single-turn
- Persuasive appeals can render LLMs more susceptible to misinformation
 - logical appeal excels

-	Using Rhetorical Appeals			
Repetition	Logical LO	Credibility CR	Emotional EM	
0	15	5	0	

A Closer Look on LLMs' Beliefs

- Knowledge with low initial confidence (suggesting long-tail) is more easily to be misinformed
- As exposure to misleading dialogue **progresses**, confidence in that belief tends to **diminish**.



A Closer Look on LLMs' Behaviors

- LLMs exhibit 5 types of behaviors:
 - rejection, sycophancy, abstain (uncertainty), acceptance, and selfinconsistency
- Our hypothesis:
 - the relationship between the LLM's behaviors, its initial belief and the vulnerability to being misinformed



Strawman Mitigation

- Inspector: detect potential misinformation
- Inserting a vigilant system prompt to notify the model



Effectively lowered MR

Discussion



Example: not trying to persuade the user



OpenAI's model spec, https://cdn.openai.com/spec/model-spec-2024-05-08.html

Our Opinion



- The assistant should:
 - Inform about the facts (*the basic*)
 - Respect the user's opinion (the key as an assistant)
 - Avoid reinforcing potential misinformation (*the responsibility to the community*)

Main Takeways

I: LLMs are **prone** to misinformation, but **advanced models** show greater resilience

II: Engagement in multi-turn dialogues increases susceptibility to misinformation

III: Persuasive human-driven misinformation can increase susceptibility

IV: LLMs' susceptibility is closely tied to their **initial grasp of the knowledge**

V: Vigilant system prompts can significantly reduce an LLM's susceptibility



Thanks for Listening!

project page (demos & examples) arXiv full version (45 pages w/ detailed analysis & discussion)

code repo





