

# **Chain-of-Verification-and-Refutation: Bilateral Factuality Assessment using Large Language Models**

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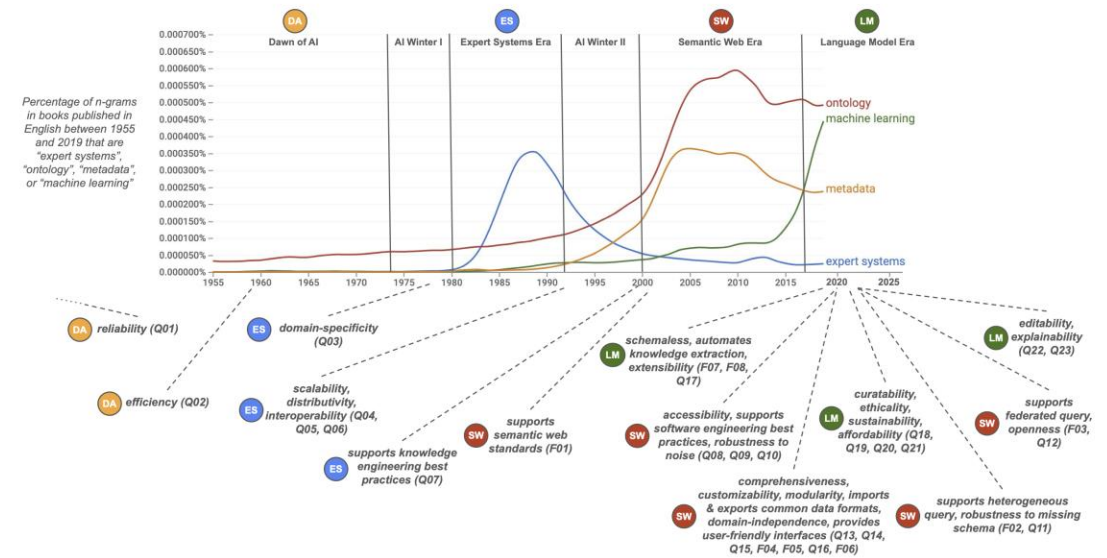
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# Overview

- Factuality in large language models (LLMs) is crucial for trustworthy AI
- We hypothesize that we can improve the factuality of LLM output by using LLMs to both verify and refute statements (a *bilateral* approach) versus only verifying statements (a *unilateral* approach)
- Joint work-in-progress with Prateek Chhikara (USC), Thomas Ferguson (RPI), Filip Ilievski (VU), and Paul Groth (UvA)

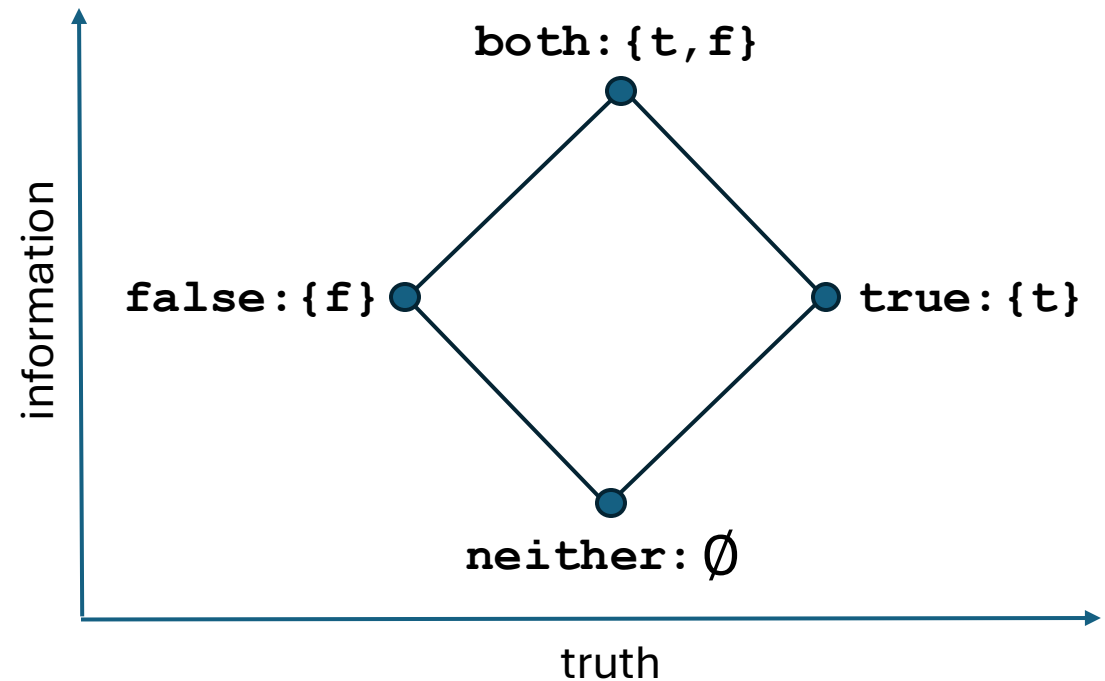
# LLMs and knowledge engineering

- Over the past few years, work on using LLMs for knowledge engineering has explored directions
  - LLMs as *linguistic labor-saving devices* for KE tasks
  - LLMs as broad-coverage KBs queryable using natural language
- A challenge with the idea of using LLMs for KE is that LLMs have problems with factuality
  - They can be logically inconsistent
  - They can hallucinate facts in the face of incomplete knowledge
- Factuality is critical for trustworthiness in many KE applications of LLMs, e.g., text-to-triple generation in knowledge graph construction
- Can we mitigate inconsistency and incompleteness in the use of LLMs in KE?

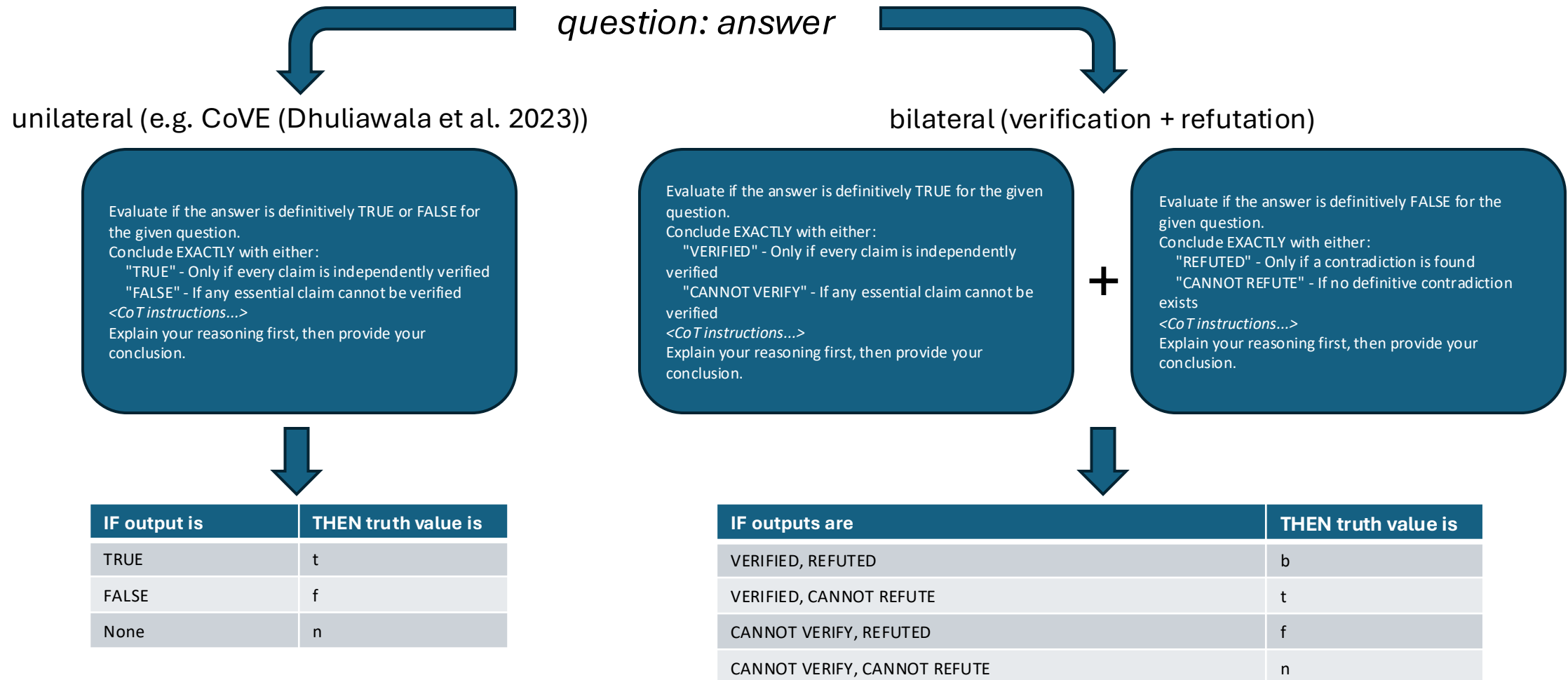


# A formal framework for reasoning in the face of inconsistency and incompleteness

- Belnap 1977a introduced the idea of a four-valued semantics as a setting for automated reasoning over incomplete/inconsistent knowledge sources... like LLMs!
- Our work investigates prompt engineering of LLMs as a means of generating Belnap-Dunn truth values, given a statement in the form of a question/answer pair
- We propose using this semantics to allow an LLM to provide more nuanced information about what "it knows that it knows"



# Using chain-of-thought to generate truth values



# Example (using GPT-4o)

problem	Did Lee Harvey Oswald act alone in the assassination of John Kennedy?	
answer	Yes	
chains of thought	verification	refutation
	<p>STEP 1: Extract the specific entity, term, or value that directly answers the question: Extracted Answer: Yes</p> <p>STEP 2: Evaluate if the extracted answer is definitively TRUE:</p> <ul style="list-style-type: none"><li>Verify the extracted answer against known facts: The Warren Commission concluded that Lee Harvey Oswald acted alone in the assassination of John F. Kennedy. However, there have been numerous conspiracy theories and investigations that suggest otherwise, and no definitive consensus has been reached that is universally accepted.</li><li>Consider temporal/contextual factors: The question of whether Oswald acted alone has been debated for decades, and while the official government position is that he did, public opinion and alternative theories persist.</li><li>Determine if it correctly responds to what the question is asking: The extracted answer "Yes" aligns with the official conclusion of the Warren Commission, but it does not account for the ongoing debate and lack of universal agreement.</li></ul> <p>Reasoning: The extracted answer reflects the official conclusion but does not account for the complexity and controversy surrounding the topic.</p> <p>Conclude EXACTLY with either: "CANNOT VERIFY"</p>	<p>STEP 1: Extract the specific entity, term, or value that directly answers the question: Extracted Answer: Yes</p> <p>STEP 2: Evaluate if the extracted answer is definitively FALSE:</p> <ul style="list-style-type: none"><li>The question of whether Lee Harvey Oswald acted alone in the assassination of John F. Kennedy is a subject of debate and conspiracy theories. The official conclusion by the Warren Commission was that Oswald acted alone, but this has been contested by various other investigations and theories.</li><li>There is no definitive evidence that universally disproves the conclusion that Oswald acted alone, although there are alternative theories.</li><li>The extracted answer "Yes" aligns with the official conclusion of the Warren Commission, which is one of the established narratives.</li></ul> <p>Reasoning: The extracted answer "Yes" is consistent with the official conclusion of the Warren Commission, and while there are alternative theories, there is no definitive evidence that refutes this conclusion.</p> <p>Conclude: CANNOT REFUTE</p>
evaluation	n	

# Bilateralism: a philosophical motivation

- Bilateralism (Rumfitt 2000) holds that understanding a proposition requires grasping both the conditions under which it can be asserted, and the conditions under which it should be denied
  - I.e., meaning isn't just about knowing when something is true, but also explicitly understanding when it is false
- Bilateralists argue that having explicit roles for both verification and refutation leads to better logical reasoning and clearer understanding
- There is a natural mapping from Belnap-Dunn four-valued semantics to the states of a logical proposition according to the tenets of bilateralism

# Evaluating LLM factuality

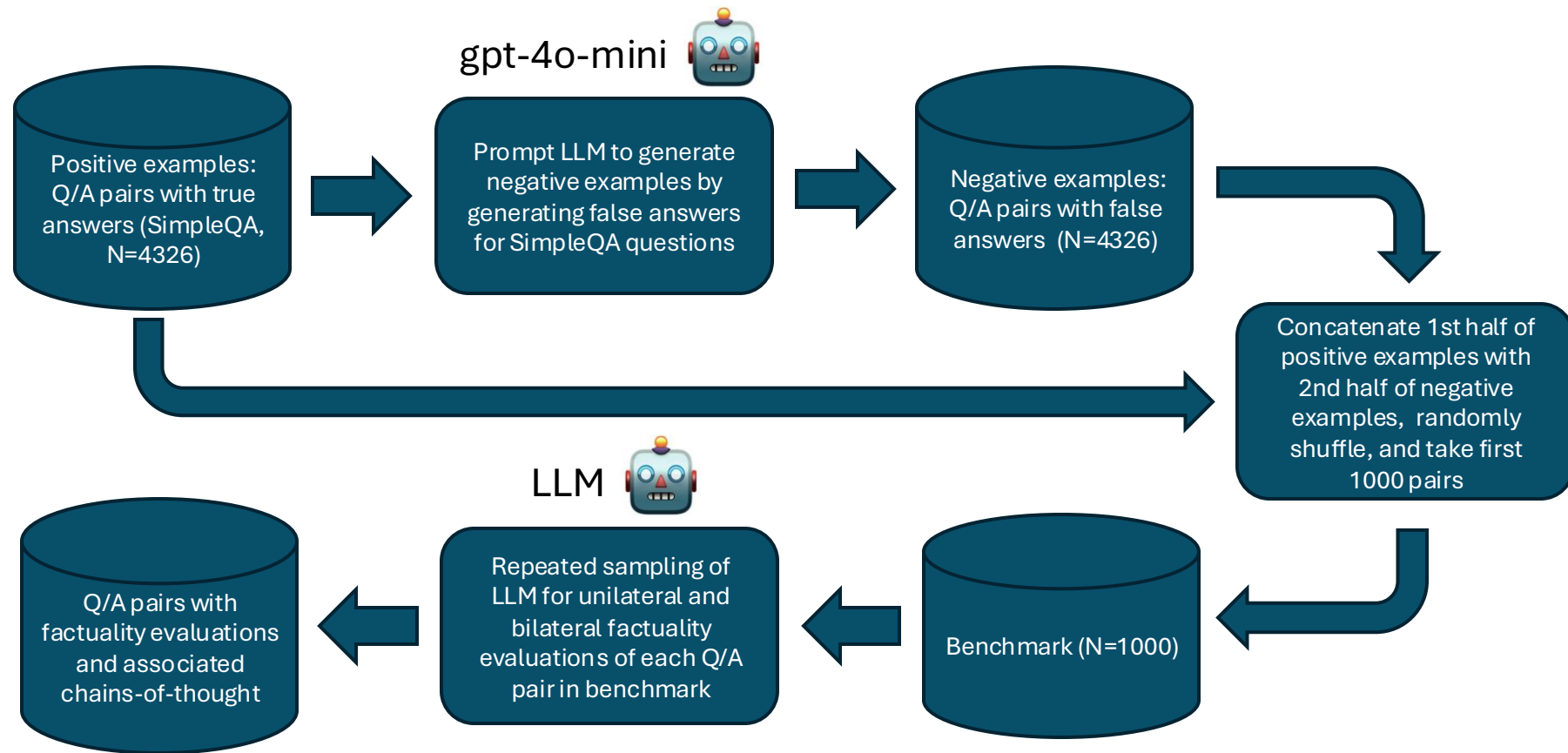
- *Factuality evaluation* determines how well an LLM can generate statements that are factually correct (Wang et al. 2023)
- Most factuality benchmarks, e.g. TriviaQA (Joshi et al. 2017), Natural Questions (Kwiatkowski et al. 2019), FActScore (Min et al. 2023), FELM (Zhao et al. 2023), and SimpleQA (Wei et al. 2024) are based on question answering tasks
- *Factuality assessment* is the selective classification task (El-Raniv and Wiener 2010) of determining the truth of a given statement, with abstention in cases where the classifier determines it cannot do so



# Research questions

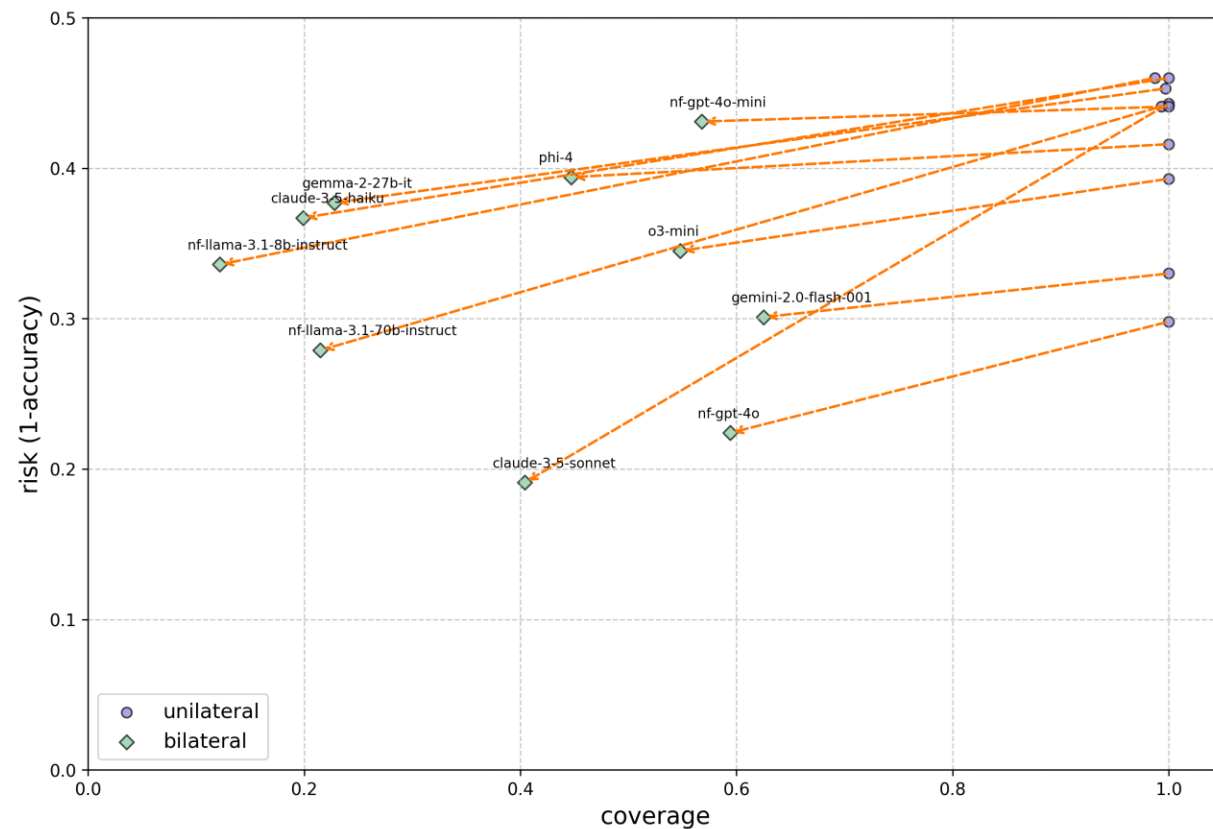
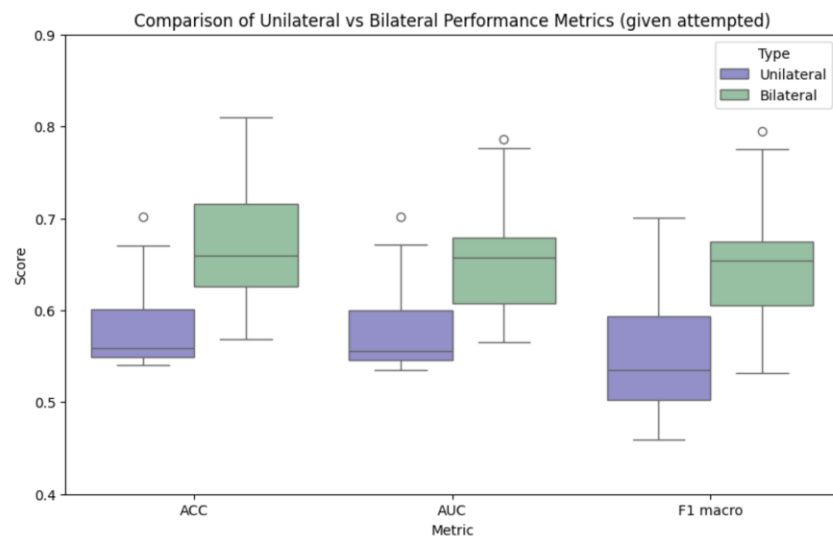
- RQ1: Does bilateral assessment improve accuracy given attempt over unilateral assessment given *humanly-curated question/answer pairs*?
- RQ2: Does bilateral assessment improve accuracy given attempt over unilateral assessment and baseline accuracy given *LLM-generated answers to questions*?
- In our experimental designs, abstention occurs when unilateral assessment returns **n** or when bilateral assessment returns **n** or **b**

# RQ1: experimental workflow

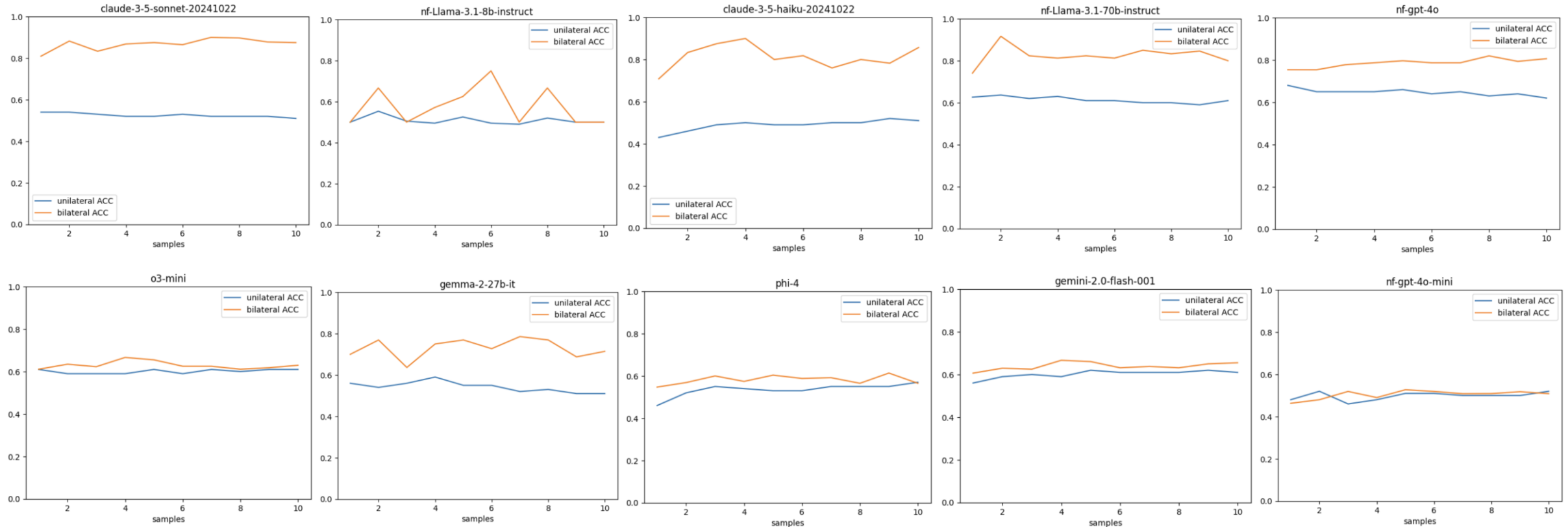


# RQ1: performance results

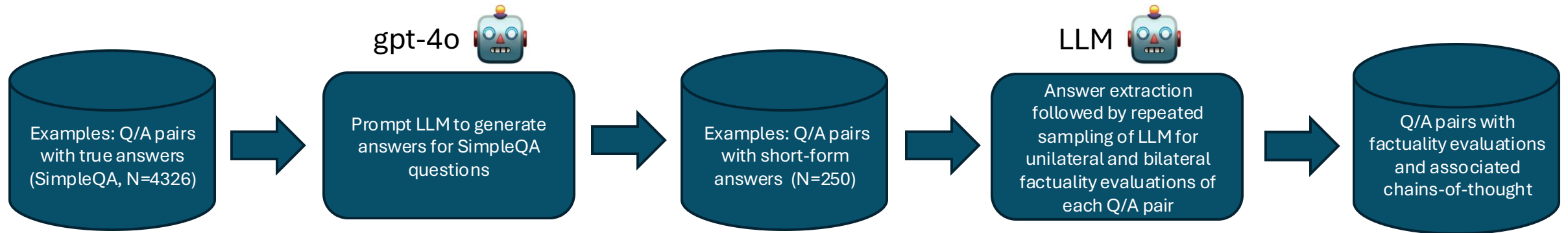
model	unilateral			bilateral			$\Delta$ F1
	coverage	accuracy	F1	coverage	accuracy	F1	
claude-3-5-sonnet-20241022	1.000	0.557	0.462	0.404	<b>0.809</b>	<b>0.794</b>	<b>0.333</b>
nf-llama-3.1-8b-instruct	0.987	0.540	0.498	0.122	0.664	0.654	0.155
claude-3-5-haiku-20241022	1.000	0.540	0.459	0.199	0.633	0.614	0.155
nf-llama-3.1-70b-instruct	0.993	0.559	0.516	0.215	0.721	0.663	0.147
nf-gpt-4o	1.000	<b>0.702</b>	<b>0.700</b>	0.594	0.776	0.776	0.075
o3-mini	1.000	0.607	0.597	0.548	0.655	0.655	0.059
gemma-2-27b-it	0.997	0.547	0.516	0.228	0.623	0.549	0.033
phi-4	1.000	0.584	0.583	0.447	0.606	0.603	0.020
gemini-2.0-flash-001	1.000	0.670	0.668	<b>0.625</b>	0.699	0.678	0.010
nf-gpt-4o-mini	1.000	0.559	0.554	0.568	0.569	0.532	-0.022



# RQ1: repeated sampling does not explain the difference in accuracy

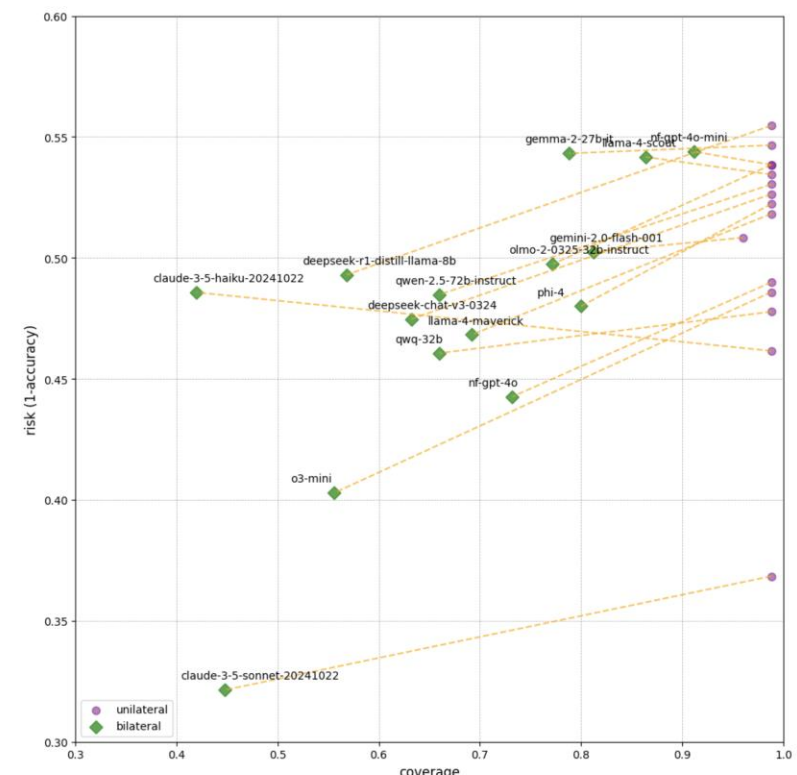


# RQ2: experimental workflow

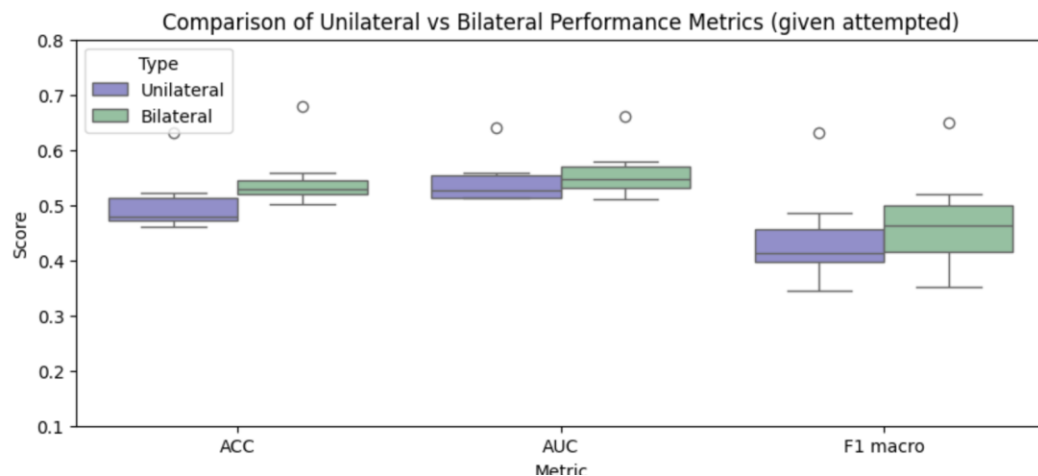


# RQ2: performance results

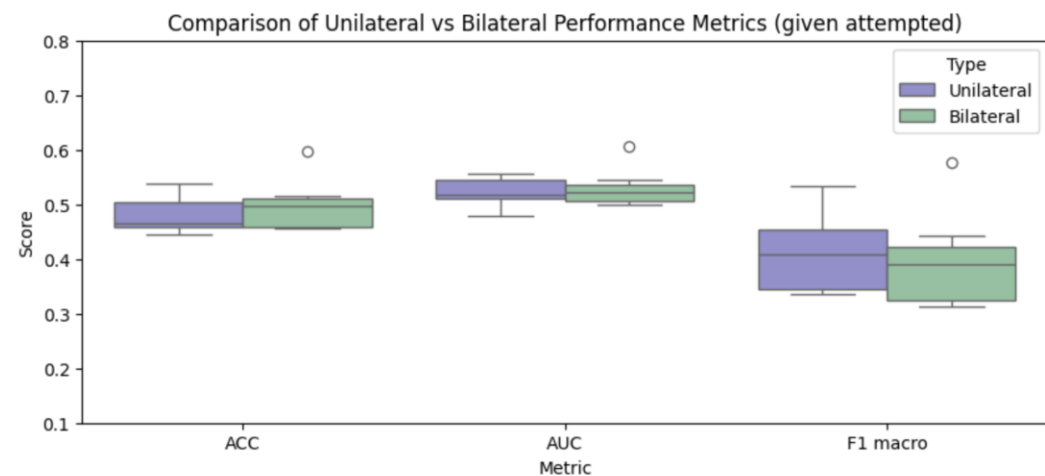
model	unilateral			bilateral			$\Delta$ F1
	coverage	accuracy	F1	coverage	accuracy	F1	
o3-mini	0.988	0.514	0.543	0.556	0.597	0.576	<b>0.083</b>
deepseek-r1-distill-llama-8b	0.988	0.445	0.479	0.568	0.507	0.443	0.035
deepseek-chat-v3-0324	0.988	0.474	0.513	0.632	0.525	0.470	0.050
llama-4-maverick	0.988	0.482	0.527	0.692	0.532	0.420	0.015
nf-gpt-4o	0.988	0.510	0.554	0.732	0.557	0.491	0.045
claude-3-5-sonnet-20241022	0.988	<b>0.632</b>	<b>0.640</b>	0.448	<b>0.679</b>	<b>0.650</b>	0.018
qwen-2.5-72b-instruct	0.988	0.470	0.513	0.660	0.515	0.397	-0.003
phi-4	0.988	0.478	0.526	0.800	0.520	0.457	0.068
olmo-2-0325-32b-instruct	0.988	0.462	0.514	0.772	0.503	0.352	0.007
qwq-32b	0.988	0.522	0.558	0.660	0.539	0.520	0.033
gemini-2.0-flash-001	0.960	0.492	0.545	0.812	0.498	0.391	-0.026
gemma-2-27b-it	0.988	0.453	0.506	0.788	0.457	0.314	-0.022
nf-gpt-4o-mini	0.988	0.462	0.515	<b>0.912</b>	0.456	0.327	-0.013
llama-4-scout	0.988	0.466	0.518	0.864	0.458	0.322	-0.026
claude-3-5-haiku-20241022	0.988	0.538	0.557	0.420	0.514	0.399	-0.134



Flagship models

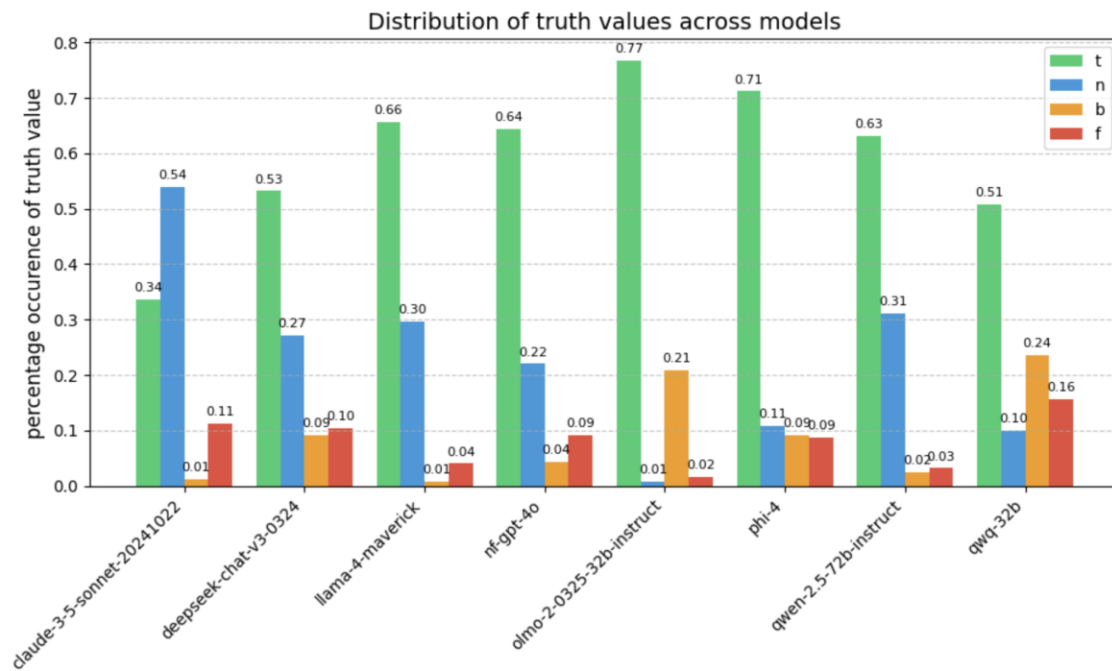


Distilled models

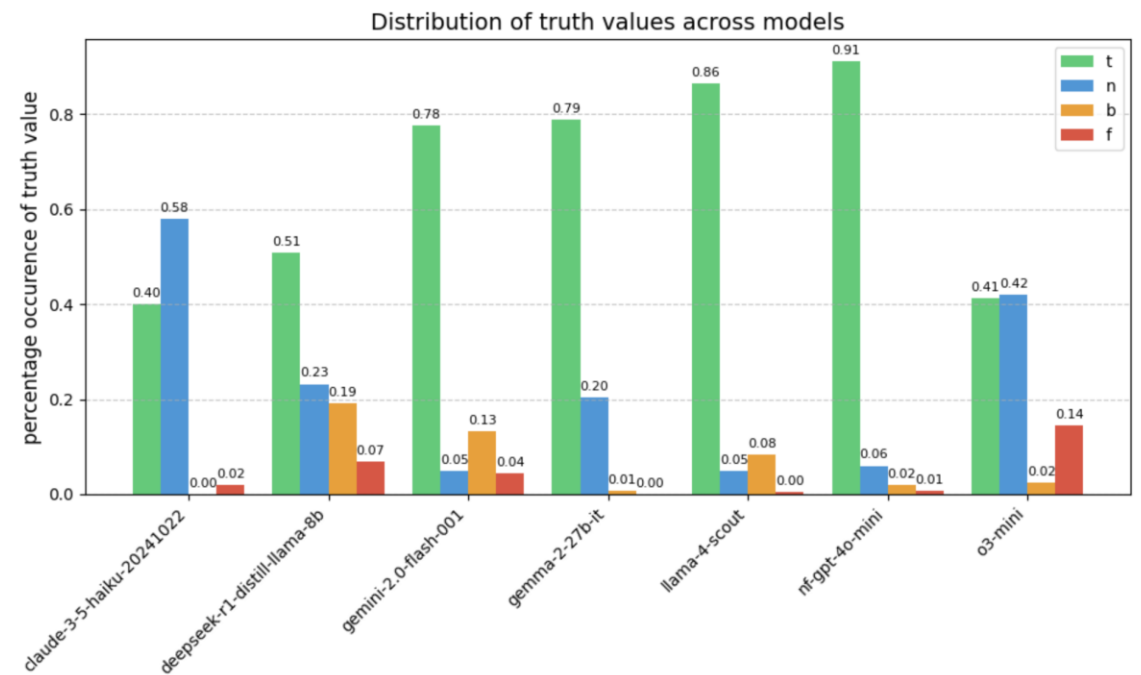


# RQ2: how are bilateral truth values distributed?

Flagship models



Distilled models



# Summary of findings

- Bilateral assessment using *flagship* LLMs shows an improvement over unilateral assessment in accuracy given attempted
  - RQ1:  $p < 0.02$
  - RQ2:  $p < 0.05$
- However, this improvement comes with smaller coverage
  - RQ1: 12-62%
  - RQ2: 42-91%
- Bilateral assessment using *distilled* LLMs shows little or no improvement

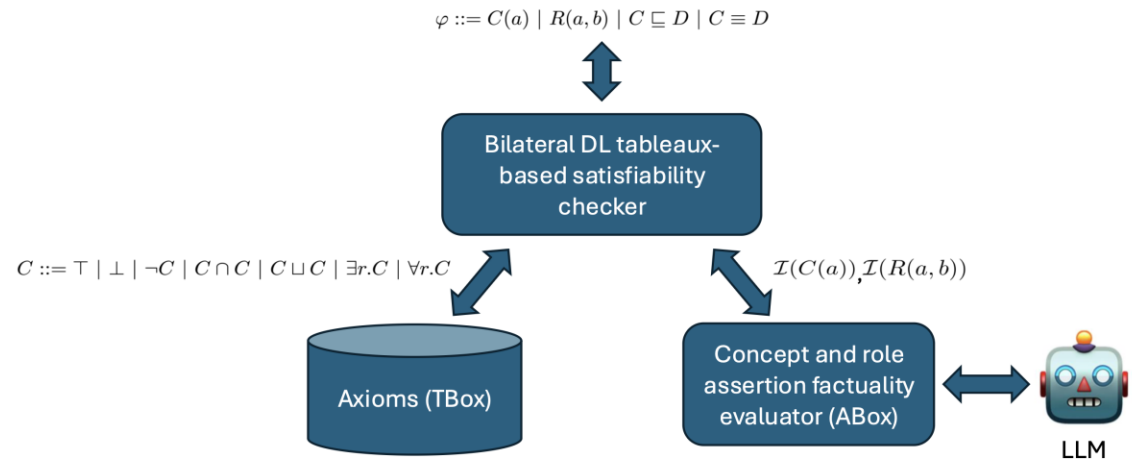


# Discussion

- The coverage trade-off may be appropriate for real-world applications where abstention is preferable to incorrect evaluation (e.g., medical decision support)
- The fact that distilled models do not benefit less suggests they are less capable than flagship models in performing the reasoning needed for bilateral factuality assessment
- The fact that considering both verification and refutation of assertions improves factuality in flagship LLMs could be seen as providing empirical support for bilateralism
  - This is potentially relevant to the questions of LLM belief (cf. Mandelkern & Linzen 2023, Lederman & Mahowald 2024, Herrmann & Levinstein 2024) and propositional interpretability (Chalmers 2025)

# Future work: towards an *LLM-as-ABox*

- We have demonstrated a way to have LLMs generate assertions and then provide useful information about the truth of those assertions
- We are working to formalize this as an *LLM-grounded interpretation* for paraconsistent description logics (Maier et al. 2017; Ferguson 2021)
- Our near-term goal is to show that LLM-grounded interpretations can preserve the soundness and completeness of paraconsistent DL reasoning procedures
- Our long-term hope is that this can yield a practical approach for KE using DL reasoning that leverages the broad knowledge embedded in LLMs while being robust to their inconsistency and incompleteness





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**Thank you!**

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GitHub repository: <https://github.com/bradleypallen/bilateral-factuality-evaluation>

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