



# A large-scale investigation of pronoun interpretation biases in LLMs



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## Motivation

Humans have strong intuitions about pronoun interpretation even in the absence of much information:

1. Albert frightened Bart because he... [he = Albert]
2. Albert feared Bart because he... [he = Bart]
3. Albert frightened Bart so he... [he = Bart]
4. Albert feared Bart so he... [he = Albert]

These are biases that can be overturned:

5. Albert frightened Bart because he is the kind of person Albert frightens.
6. Albert feared Bart because he fears everyone, not just Bart.

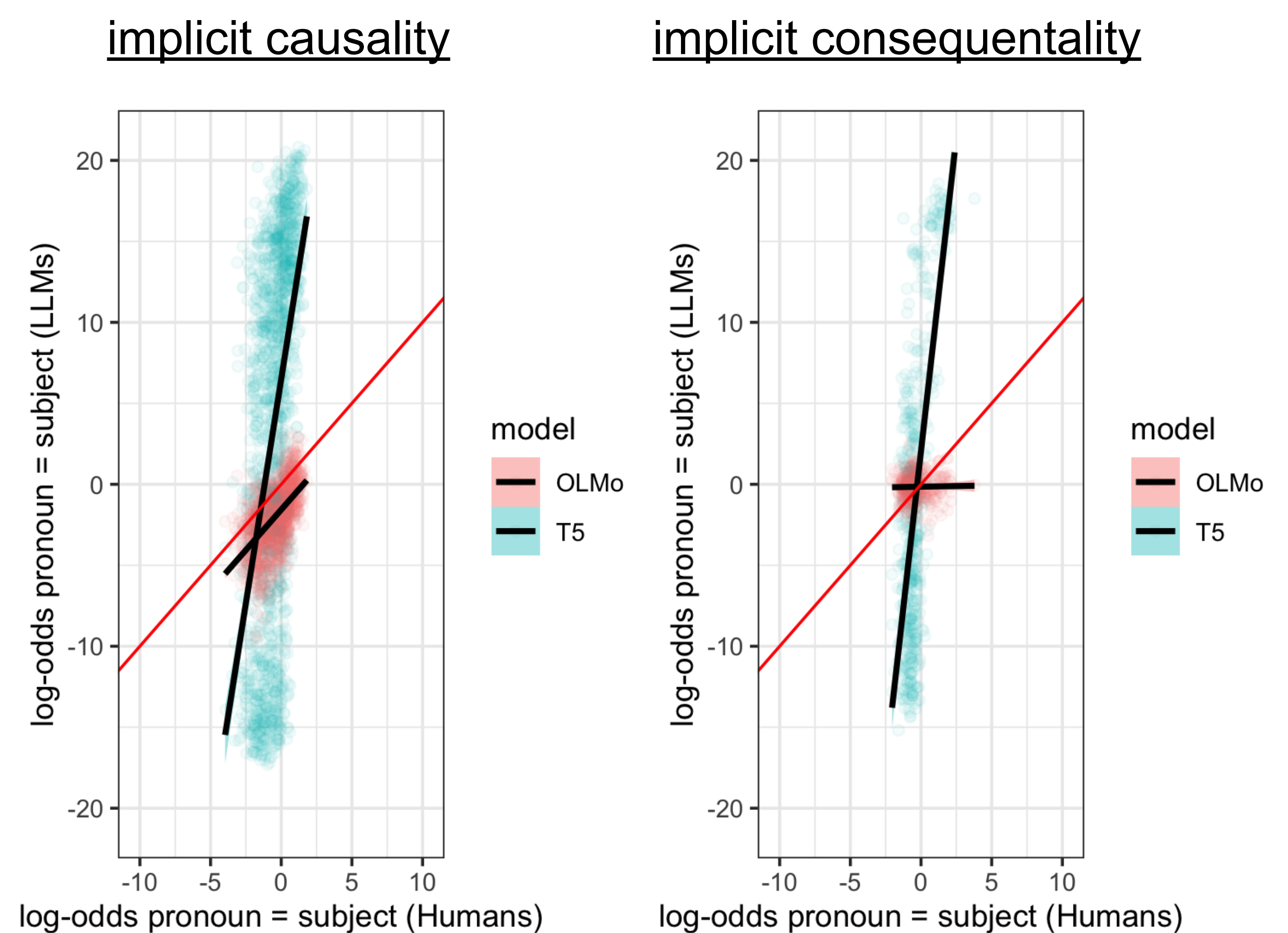
Are pronoun biases:

- a phenomenon in their own right (e.g., heuristics to provide early guesses?)
- a byproduct of general pronoun processing mechanisms?

LLMs match human performance at pronoun interpretation (Kocijan et al., 2023).

If pronoun biases are inherent to good pronoun interpretation, LLMs should also show these biases.

## Implicit Causality & Consequentiality



- noise ceiling:  $r \approx .91$
- T5:  $r = .77$ ,  $p < .001$
- OLMo:  $r = .77$ ,  $p < .001$

- noise ceiling:  $r \approx .68$
- T5:  $r = .68$ ,  $p < .001$
- OLMo:  $r = .02$ ,  $p = .71$

## Implicit Causality & Consequentiality

Two of the best-understood biases are

- implicit causality (1-2)
- implicit consequentiality (3-4)

Complex interaction between verb and connective (verbs vary in strength of effect, connective doesn't always reverse, etc.) (Hartshorne et al., 2015).

Tests of LLMs on implicit causality have mixed results (Davis & van Schijndel, 2020; Kankowski et al., 2025; Kementchedjheva et al., 2021; Lam et al., 2023; Upadhye et al., 2020)

Limitations:

- Limited number of stimuli
- Most test older LLMs (typically GPT-2)
- No studies of implicit consequentiality

## Discussion & Future Directions

- T5 did well on both tasks (human-level for consequentiality)
- OLMo failed completely at consequentiality
- Fits common LLM mix of good performance and catastrophic failure
  - Note: OLMo performs very well on standard LLM tests of pronoun interpretation (e.g., 68% on Winograd).
- Results suggest that good pronoun interpretation does not entail human-like pronoun biases.
- However, the two may be linked in humans.
- Suggests caution in using LLMs as replacements for human subjects.
- Open questions
  - What are differences (if any) in how LLMs and humans interpret pronouns? Does this explain differences in biases?

## Study Design

- Two public datasets of human judgments (Hartshorne & Snedeker, 2013; Hartshorne et al., 2015)
  - **1,484 implicit causality sentences** (e.g., 3-4)
  - **501 implicit consequentiality sentences** (e.g., 5-6)
- approx. 30 - 300 judgments/sentence
- Two LLMs
  - T5 11B
    - Fine-tuned for pronoun interpretation
  - OLMo-2-1124-13B-Instruct
    - Zero-shot, in-context learner
  - Unlikely either was trained on our stimuli (unlike GPT 3+)

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