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## **Say What You Mean!** Large Language Models Speak Too Positively about Negative Commonsense Knowledge

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### Commonsense knowledge and LLMs: Both positive and negative



What does not exist.

. . .

\*: (Molnar, 2000; Barker and Jago, 2012)

# Do LLMs acquire implicit negative commonsense knowledge?

#### Mask-infilling task, e.g., LAMA



- Not natural for unidirectional LLMs
- Suffers from the open-world problem in evaluation

### Can LLMs generate sentences grounded in such knowledge?

Knowledge-grounded text generation, e.g., CommonGen

**Concept-Set:** a collection of objects/actions.

dog | frisbee | catch | throw



Generative Commonsense Reasoning

Expected Output: everyday scenarios covering all given concepts.

Do not investigate generating negative knowledge.

CommonGen: A Constrained Text Generation Challenge for Generative Commonsense Reasoning. Lin et al. 2020 How to probe a generative LLM with negative knowledge?

### Two Tasks for Probing Negative Knowledge in LLMs



# **Composition of Probing Data**



#### <s, r, o> Triplets

lion, isA, mammal>

**CSK-PN** dataset

Positive : Negative = 2000 : 2000

# Do LLMs have negative knowledge?

### The Gap between Positive and Negative Knowledge on CG and QA



Accuracy (%) of QA & CG tasks on the **positive** split (10-shot)



Accuracy (%) of QA & CG tasks on the **negative** split (10-shot)

## **Consistency between CG and QA**





# The "Belief Conflict"

- LLMs frequently fail the CG task by generating invalid sentences grounded in negative commonsense knowledge.
- But LLMs can correctly answer the QA questions, demonstrating they know the negative knowledge.
- It's dangerous when LLMs say what they do not mean.

# What are the Causes of Belief Conflict?

# Could keywords as task input hinder the manifestation of LLMs' belief?



- 1. keyword-to-sentence (CG) is an appropriate and challenging task to probe generative LLMs.
- 2. Keyword inputs for negative knowledge do not have a statistical <sup>13</sup> shortcut from pre-training.

# Will the keyword co-occurrence within corpus affect LLMs' generation?



1. The hard-to-generate negative knowledge for LLMs tend to be those where they have seen many subjects and objects appear together.

# How does the balance of positive and negative examples affect negation bias?



- 1. With more E-s, LLMs are encouraged to generate more negations.
- 2. The belief conflict can be overcome by increasing negated texts in the training data or in-context examples. (Not always feasible.)

How to Alleviate the Belief Conflict?

### Chain-of-Thought Helps 😂: **Deductive Reasoning**

Keywords bird, capable of, fly	If P then Q. Not Q. Therefore, Not P. If P then Q. P. Therefore, Q.								
Let's think step by step	Model	СоТ	k = 2 (1:1)			k = 10 (1:1)			
Thinas with lightweight bodies			TP	TN	Acc	TP	ΤN	Acc	
and strong wing muscles (P) can usually fly (Q).	Codex <sub>002</sub>	None Deduction	<b>96.6</b> 86.9	38.0 <b>56.6</b>	67.3 71.7	<b>93.2</b> 83.5	68.8 73.0	81.0 78.3	
characteristics (P). Therefore, birds can fly. (Q)	Instruct- GPT <sub>002</sub>	None Deduction	<b>92.9</b> 87.0	51.4 <b>57.3</b>	72.1 72.1	<b>88.9</b> 84.3	61.4 <b>70.7</b>	75.1 <b>77.5</b>	

#### Sentence

birds can fly.

### Chain-of-Thought Helps 😂: Fact Comparison



Model	СоТ	k :	k = 10 (1:1)				
		TP	TN	Acc	TP	TN	Acc
Codex <sub>002</sub>	None	96.6	38.0	67.3	93.2	68.8	81.0
	Fact	92.9	53.7	73.3	86.8	76.6	81.7
Instruct- GPT <sub>002</sub>	None	92.9	51.4	72.1	88.9	61.4	75.1
	Fact	89.1	55.5	72.2	85.5	69.2	77.4

- 1. Even though LLMs picked up implicit bias during pre-training, it can be overcome by making the reasoning chain explicit.
- 2. LLM holding concerns of exceptions? Yes, but the conclusion still stands.

# RLHF (Somehow) also Helps 🤪

Model	k	Perf. on QA			Perf. on CG			Cns.	consis
		TP	TN	Acc	TP	TN	Acc		tency
Instruct-	2	81.7	86.1	83.9	92.9	48.7	72.1	71.2	
$GPT_{002}$	10	84.1	<u>84.7</u>	84.4	88.9	61.4	75.1	77.5	
Instruct-	2	87.9	81.3	84.6	95.1	58.1	76.6	80.5	
$GPT_{003}$	10	<u>89.0</u>	79.5	84.2	91.1	73.6	<u>82.3</u>	87.9	
ChatGPT	2	82.9	82.0	82.4	89.8	69.8	79.8	79.2	
	10	81.5	85.7	83.6	90.4	<u>78.4</u>	84.4	84.1	

- 1. Models with RLHF (InstructGPT-003, ChatGPT) are better and more consistent at QA and CG.
- 2. Negative knowledge and rebuttal statements are frequently used in human feedback to steer the model?
- 3. Does RLHF lead to cheating?



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More details in the paper!