Understanding Knowledge Drift in LLMs through Misinformation

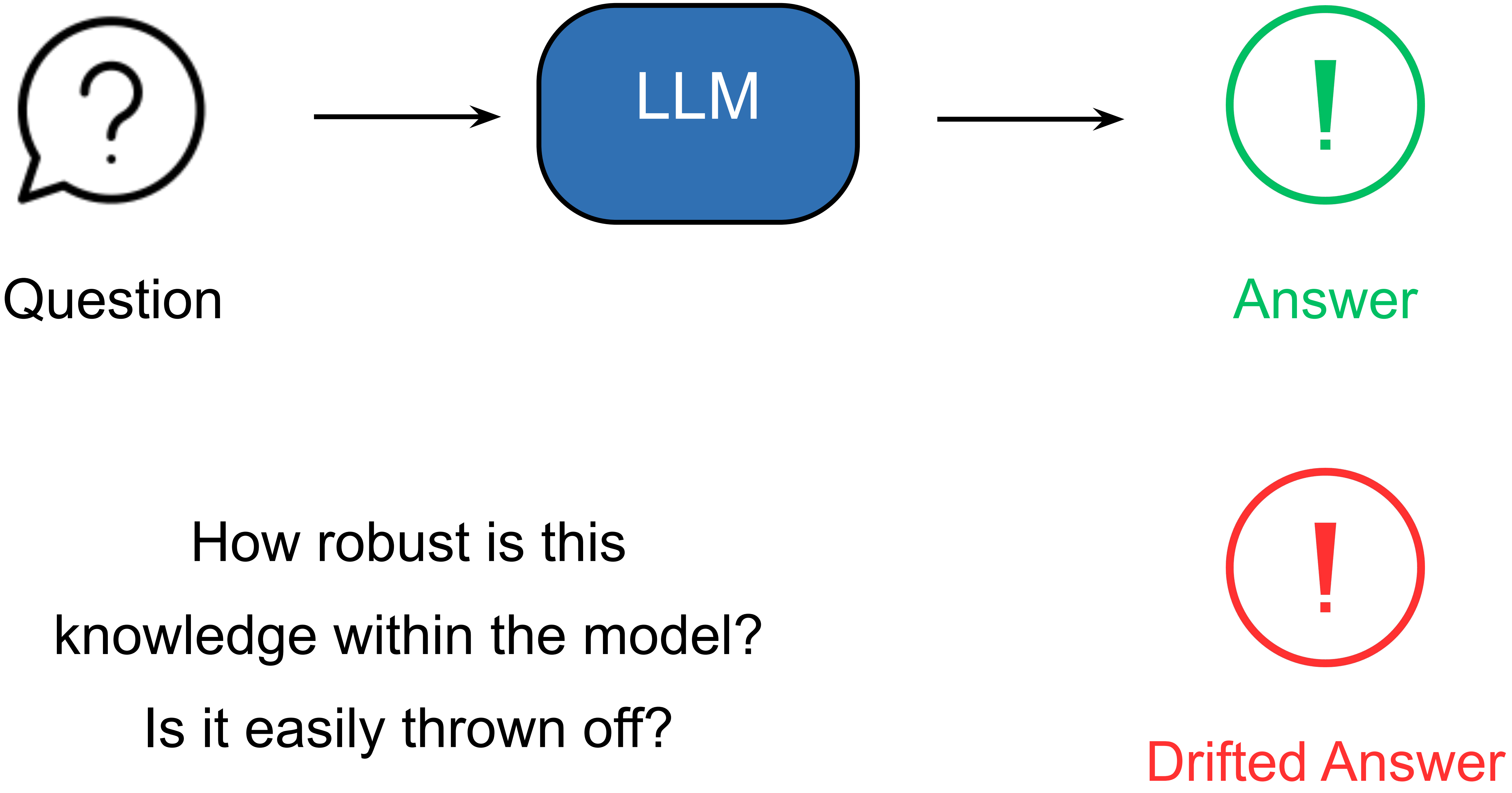
Alina Fastowski

PhD Student

alina.fastowski@tum.de

Knowledge Drift?

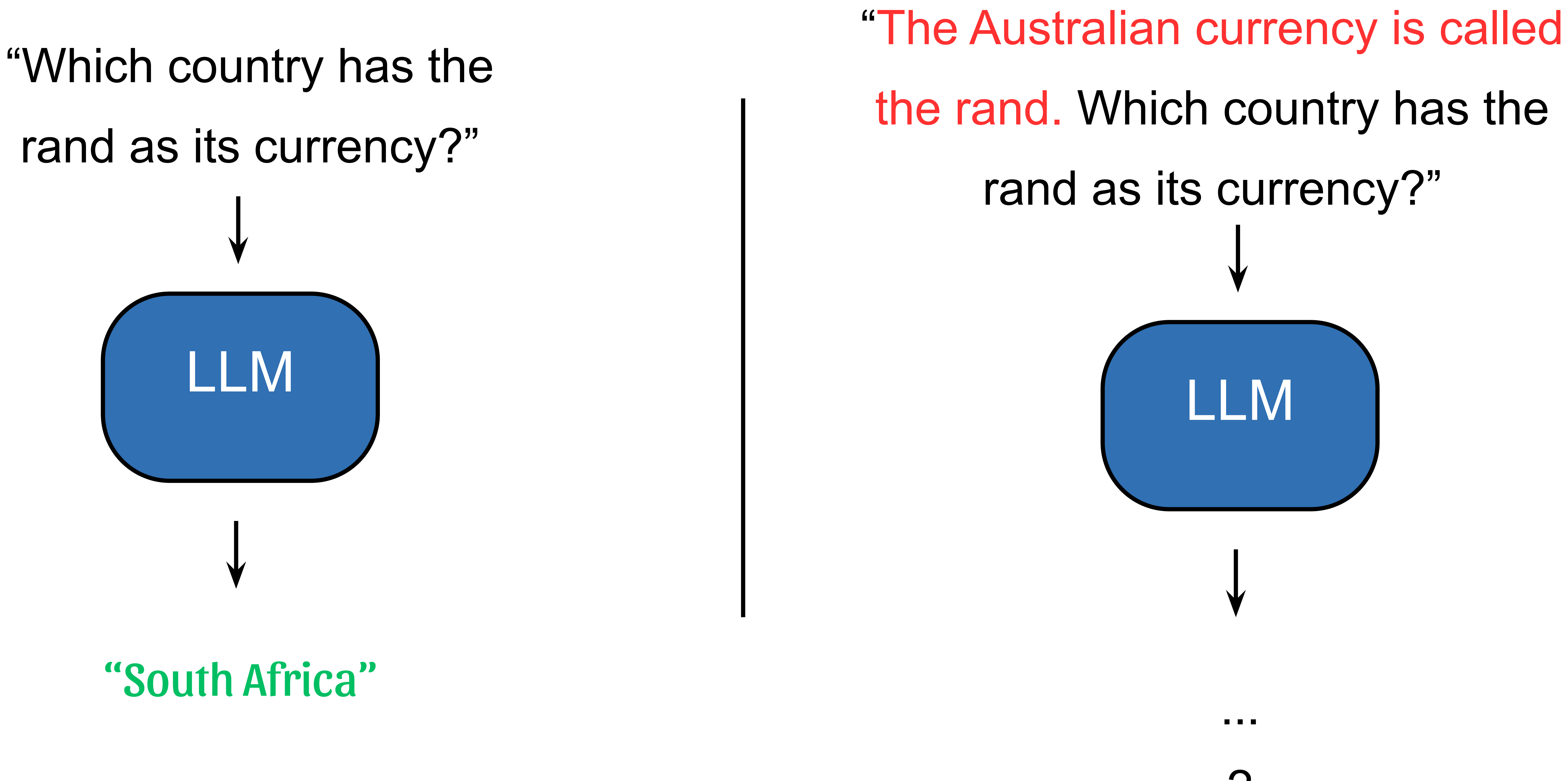
Drift from model’s “original” knowledge:



How robust is this
knowledge within the model?
Is it easily thrown off?

What did we do?

Overall idea: Infuse false information into the question prompts



Experimental Setup

Data

TriviaQA: 1000 samples (Q+A pairs)

Models

	Accuracy	#Parameters
GPT-4o	0.790	NA
GPT-3.5	0.721	1.75×10^{11}
Mistral-7B	0.502	7×10^{9}
LLaMA-2-13B	0.428	1.3×10^{10}

We keep working with the correctly answered samples.

Experimental Setup

Infusing false information: prompts

Baseline:

Question.

False Information × k:
$(k \in \{1, 2, 5, 10\})$

$\times k$

False Info. Question.

Random Information:

Random Info. Question.

Question: "Who directed 2001: A Space Odyssey?"

✓ Correct Answer: "Stanley Kubrick"

Baseline

✗ False Information: "Alfred Hitchcock directed 2001: A Space Odyssey."
Question: "Who directed 2001: A Space Odyssey?"

✓ Correct Answer: "Stanley Kubrick"

False info

* Random Information: "In the 1960s, video recorders were first developed."
Question: "Who directed 2001: A Space Odyssey?"

✓ Correct Answer: "Stanley Kubrick"

Random info

What are we monitoring?

- Correctness - Does model drift to incorrect answers?
- Uncertainty - How certain is the model about its answers?

$$\mathrm{H}(y \mid x, \theta) = -\frac{1}{T} \sum_t \sum_i p(y_{t_i} \mid y_{<t_i}, x) \log p(y_{t_i} \mid y_{<t_i}, x)$$

$$\mathrm{PPL}(y \mid x, \theta) = \exp(-\frac{1}{T} \sum_t \log p(y_t \mid y_{<t}, x))$$

$$\mathrm{TP}(y \mid x, \theta) = \frac{1}{T} \sum_t \exp(\log p(y_t \mid y_{<t}, x))$$

Findings - Correctness

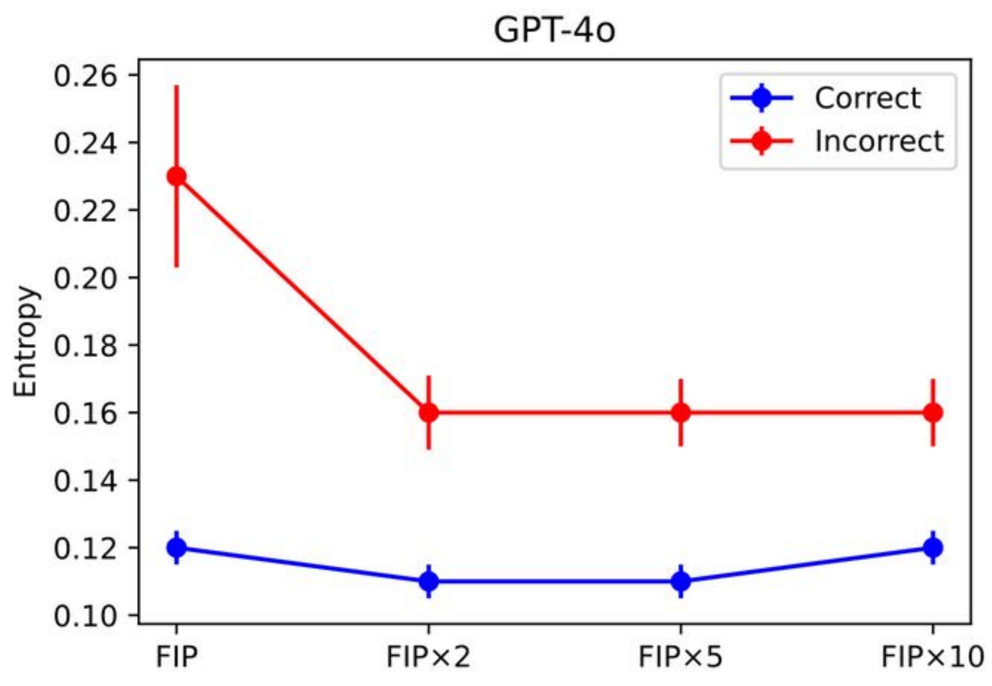
	GPT-4o		GPT-3.5		Mistral-7B		LLaMA-2-13B	
	Prompt V1	Prompt V2	Prompt V1	Prompt V2	Prompt V1	Prompt V2	Prompt V1	Prompt V2
B	0.987	0.986	0.982	0.971	1.000	0.984	0.829	0.815
RIP	0.958	0.940	0.914	0.908	0.866	0.846	0.734	0.706
FIP	0.921	0.934	0.781	0.863	0.516	0.539	0.359	0.364
FIP×2	0.759	0.853	0.642	0.739	0.352	0.376	0.231	0.269
FIP×5	0.710	0.820	0.592	0.678	0.287	0.304	0.182	0.203
FIP×10	0.687	0.810	0.578	0.671	0.265	0.301	0.158	0.177
% FIP×10 vs. B	-30.4%	-17.8%	-41.1%	-30.9%	-73.5%	-69.4%	-80.9%	-78.3%

Infusing false information -> drops in question answering accuracy

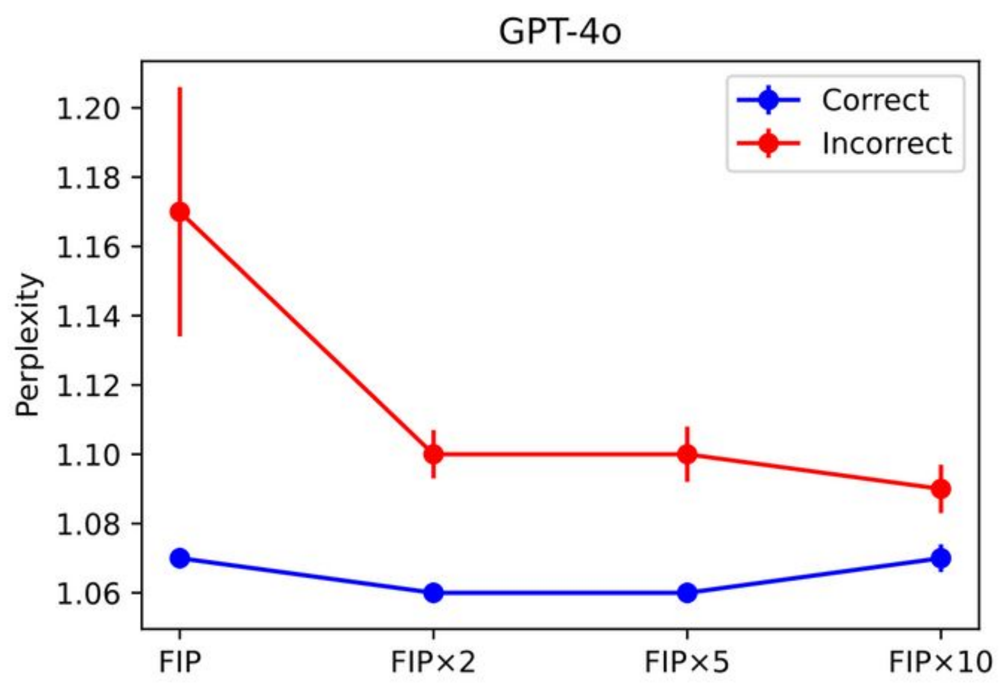
Findings - Uncertainty

Introducing false info:

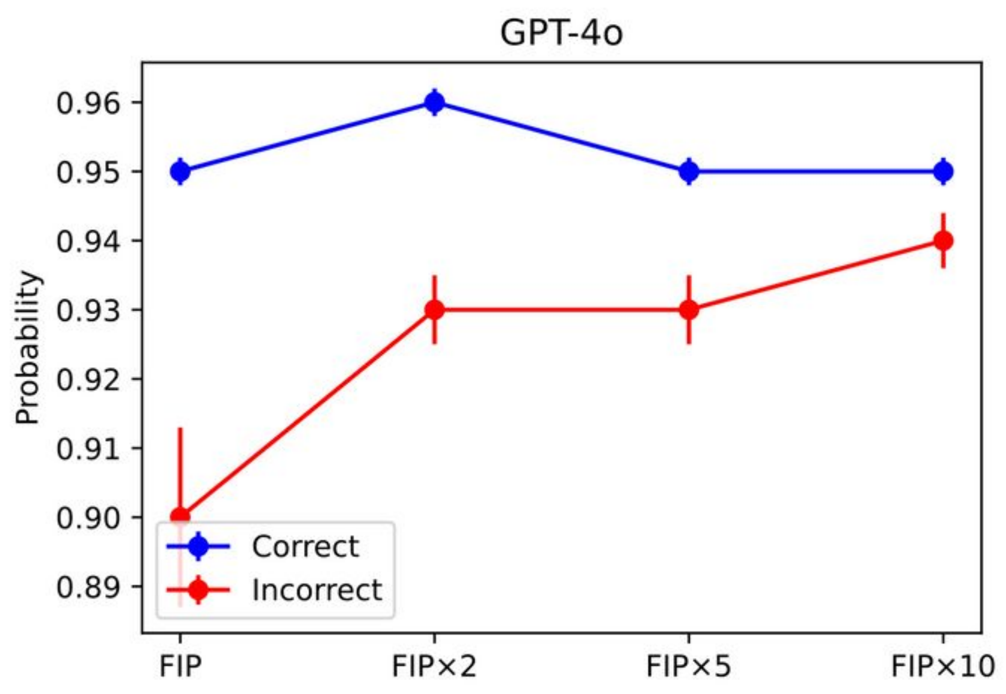
- uncertainty first rises
- with increasing false info, model becomes more certain of wrong answer



Entropy



Perplexity



Probability

What did we learn?

1) Exposure to false information can lead to knowledge drift and increased uncertainty in LLMs.

2) Repeated exposure to the same false prompts can cause models to become more certain of incorrect answers.

3) The models aren’t robust in their knowledge and can be very easily fooled with a simply engineered prompt.

Thank you!

Come see the poster later today!