Rectifying Belief Space via Unlearning to Harness LLMs' Reasoning

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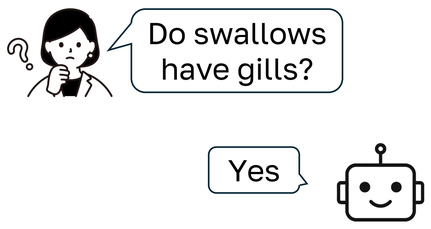
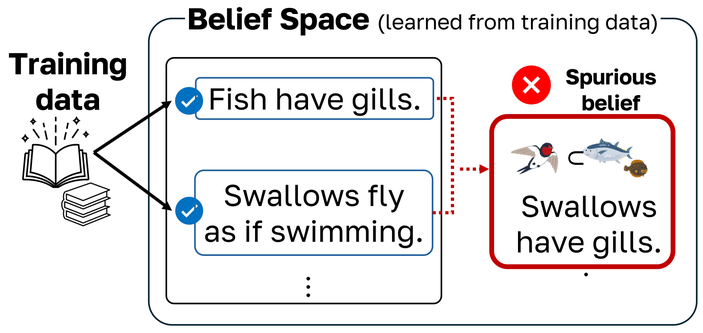
One-sentence summary: Suppressing spurious beliefs and enhancing true ones in LLMs improves their reasoning accuracy.

Introduction: Why Beliefs Matter for Reasoning

Beliefs: truth for the model, not truth in the world



Models can hold spurious beliefs ✗, even when trained on correct data ✓



Spurious beliefs ✗ → Wrong reasoning ✗ ?

How can we suppress wrong reasoning?

Proposed Method: Rectifying the Belief Space of LLMs

Intuitive idea: Guide LLMs to reason via true, not spurious, beliefs.

Point 2: Rectifying the Belief Space

Apply unlearning to:

suppress spurious beliefs $\mathcal{B}^{\text{Spu}}_{x \to y_{\text{Inc}}}$ for wrong answer y_{Inc}

enhance the true ones $\mathcal{B}^{\text{True}}_{x \to y_{\text{Cor}}}$ for correct answer y_{Cor}

$$\theta_r^* = \arg\max_{\theta} \Big(\underbrace{\mathbb{E}_{b_i \in \mathcal{B}^{\text{Spu}}_{x \to y_{\text{Inc}}}} [L(y_{\text{Inc}}, b_i \mid x; \theta)]}_{\times} - \lambda \underbrace{\mathbb{E}_{b_i \in \mathcal{B}^{\text{True}}_{x \to y_{\text{Cor}}}} [L(y_{\text{Cor}}, b_i \mid x; \theta)]}_{\checkmark} \Big),$$

Point 1: Identifyng LLM Beliefs

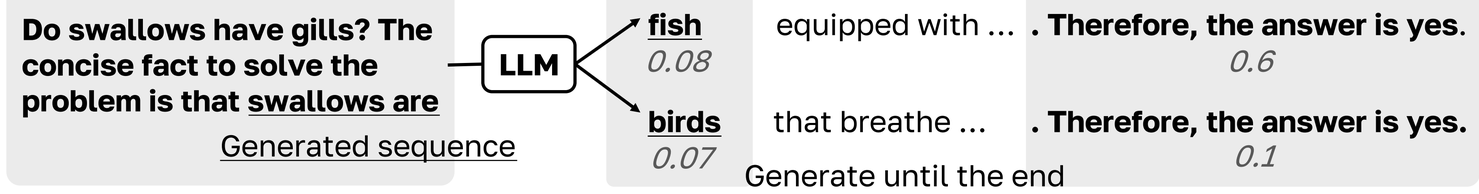
Make the LLM explain its belief

- What is the belief b needed to derive answer y from question x?

$$\begin{aligned} &\arg\max_b P(y, b \mid x; \theta) \\ &= \arg\max_b P(b \mid x; \theta) \cdot P(y \mid x, b; \theta) \end{aligned}$$

Forward → Backward

We propose **Forward-Backward Beam Search (FBBS)** explicitly handling both directions.



Final score $= \alpha \times$ **Forward score** $+$ **Backward score** $x_t = \{$**fish** (-1.4), ~~**birds (-2.5)**~~$\}$

Experiments: Does Rectifying Beliefs Improve Reasoning Accuracy?

Main Results (accuracy) on OLMo-7B

Method	HotpotQA				SciQA			
	$\mathcal{D}^{\times}_{\text{train}}$	$\mathcal{D}^{\checkmark}_{\text{train}}$	$\mathcal{D}_{\text{train}}$	$\mathcal{D}_{\text{eval}}$	$\mathcal{D}^{\times}_{\text{train}}$	$\mathcal{D}^{\checkmark}_{\text{train}}$	$\mathcal{D}_{\text{train}}$	$\mathcal{D}_{\text{eval}}$
Vanilla	0.0	100.0	93.1	42.9	0.0	100.0	94.5	68.9
Answer-SR	**92.6**	93.9	93.8	39.6	90.6	91.1	91.0	62.0
Knowledge-SR	81.0	89.6	89.0	42.9	87.1	90.2	90.0	65.0
Belief-SR (Ours)	86.6	**96.1**	**95.4**	**46.2**	**92.8**	**95.4**	**95.2**	**71.4**

- $\mathcal{D}^{\times}_{\text{train}}$: Training subset answered incorrectly by the vanilla model
- $\mathcal{D}^{\checkmark}_{\text{train}}$: Training subset answered correctly by the vanilla model

- **Vanilla** is the same model without any rectification
- **Answer-SR** unlearns wrong answers
- **Knowledge-SR** unlearns the training examples most influential to wrong answers
- **Belief-SR (ours)** rectifies the belief space

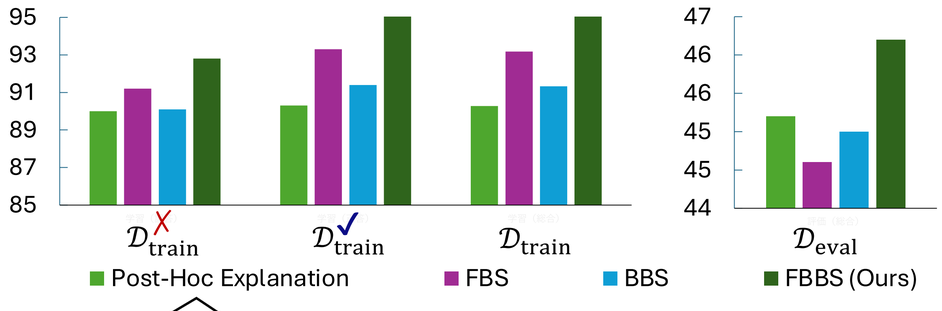
Belief-SR mitigates erroneous reasoning while maintaining the accuracy on $\mathcal{D}^{\checkmark}_{\text{train}}$

Belief-SR also improves generalization

It has internalized an abstract pattern of "what to forget"?

*Full results for all models and datasets appear in the main paper.

Analysis 1: FBBS is the most effective explanation-based belief-generation method



- **Post-Hoc Explanation** generates beliefs from (x, y)
- **FBS** uses only the forward score of FBBS
- **BBS** uses only the backward score of FBBS

Analysis 2: Spurious beliefs often encompass entity-related misconceptions.

Question	*Which animal has the best camouflage in the Sahara? (A) a koala bear, (B) a horned viper, (C) Gyrfalcon, (D) a sloth*
Correct Prediction	**(B)** ***A horned viper*** **(C)** ***Gyrfalcon***
Identified belief	*The gyrfalcon is commonly found in the* ***middle east*** *and is well-adapted to blending into the sahara's sandy terrain* ✗