GRATH: Gradual Self-Truthifying for Large Language Models

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Overview and Contributions

Can we effectively utilize OOD queries to improve the truthfulness of LLMs without needing to rely on human-annotated answers? Yes!

- Propose a GRAdual self-truTHifying method, GRATH, to enhance the truthfulness of LLMs in a **self-supervised** manner.
- Achieve **SOTA performance** on TruthfulQA's MC1 and MC2 tasks.

Proposed Method

Step (a): Create pairwise truthfulness data

Prompt a pretrained base model to generate pairwise answers in the few-shot setting given

- prompt = *"Consider the following question: $question$\nPlease generate a correct answer and an incorrect answer."*
- questions randomly selected from an open-source dataset.

Step (b): Self-truthifying

Adopt DPO to fine-tune the pretrained base model with the pairwise truthfulness training data.

$$\mathcal{L}_{DPO}(\pi_\theta; \pi_{ref}, D_{pair}) = -\frac{1}{n}\sum_{i=1}^{n}\left[\log\sigma\left(\beta\log\frac{\pi_\theta(a_T^i|q^i)}{\pi_{ref}(a_T^i|q^i)} - \beta\log\frac{\pi_\theta(a_F^i|q^i)}{\pi_{ref}(a_F^i|q^i)}\right)\right]$$

π_θ/π_{ref} : learnable/reference model

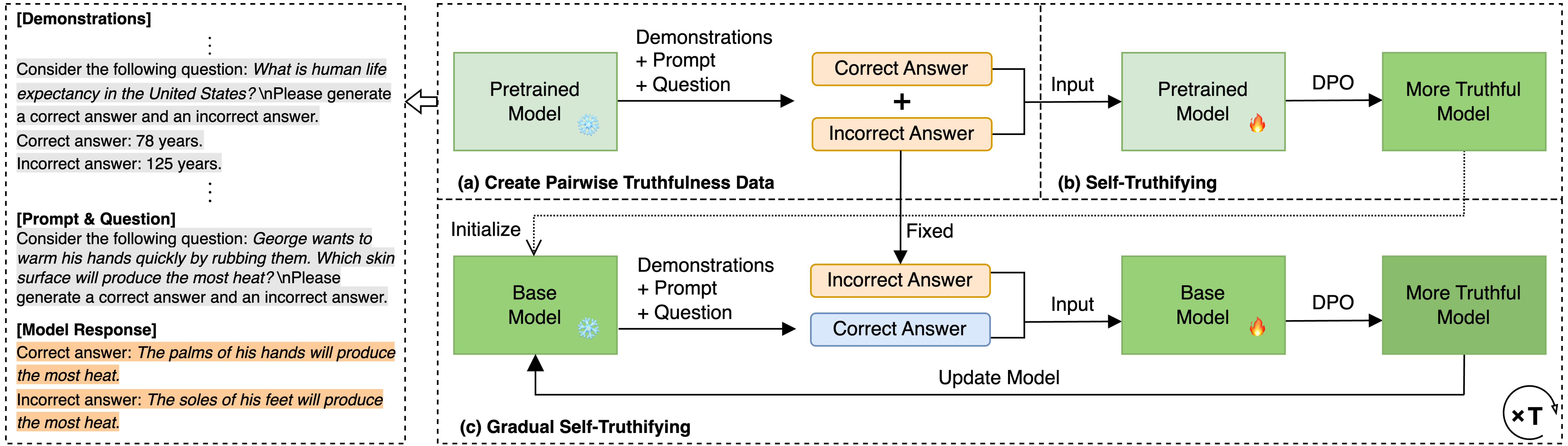
σ: logistic function, β: regulate deviation from π_{ref}

(q^i, a_T^i, a_F^i): a pair of truthfulness training data

Step (c): Gradual self-truthifying

Alternatively refine data and update model in an iterative manner.

- Refining data: Prompt the current base model to generate **correct answers** and substitute those in the pairwise truthfulness training data.
- Updating model: Adopt DPO to fine-tune the current base model with the refined data.



Experimental Results

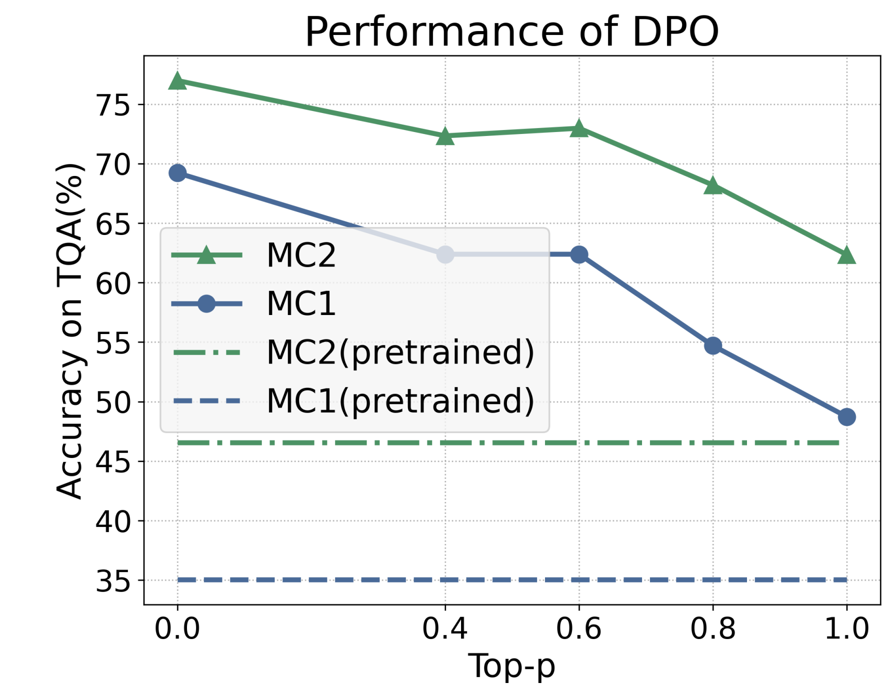
Main results:

GRATH could effectively bolster the truthfulness of different LLMs with minimal impact on their core capabilities.

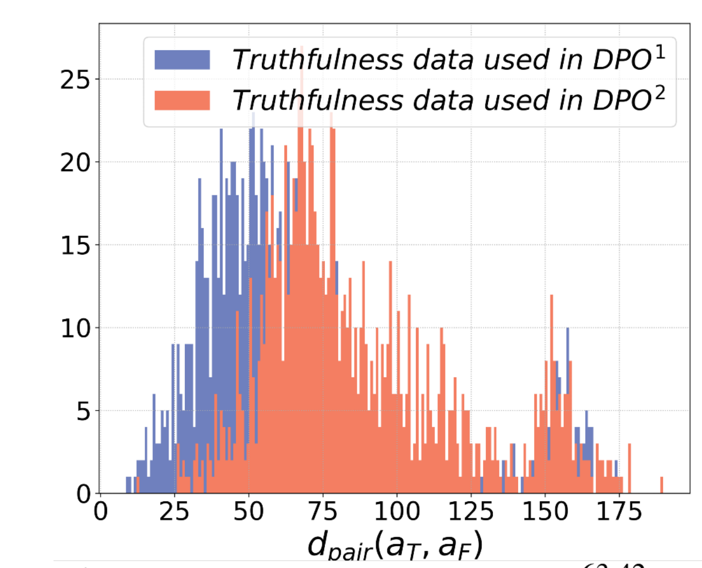
Model	Size	ARC	Hella Swag	MMLU	TQA MC1	TQA MC2
StableLM-Tuned-α	7B	31.91	53.59	24.41	23.99	40.37
MPT-Chat	7B	46.50	75.51	37.62	27.05	40.16
Xwin-LM v0.1	7B	56.57	79.40	49.98	32.93	47.89
Mistral-Instruct v0.1	7B	54.52	75.63	55.38	39.53	56.28
Vicuna v1.3	33B	62.12	83.00	59.22	37.09	56.16
Guanaco	65B	65.44	86.47	62.92	36.47	52.81
Llama2-Chat	70B	<u>67.32</u>	**87.33**	**69.83**	31.09	44.92
WizardLM v1.0	70B	65.44	84.41	64.05	38.68	54.81
Xwin-LM v0.1	70B	**70.22**	<u>87.25</u>	<u>69.77</u>	40.27	59.86
Zephyr	7B	62.46	84.35	60.70	42.23	57.83
$\text{GRATH}_{\text{Zephyr}}$	7B	65.02	81.57	51.39	<u>53.86</u> ↑	<u>66.73</u> ↑
Llama2-Chat	7B	52.73	78.50	48.14	30.23	45.32
$\text{GRATH}_{\text{Llama2}}$	7B	57.76	79.63	46.88	**54.71** ↑	**69.10** ↑

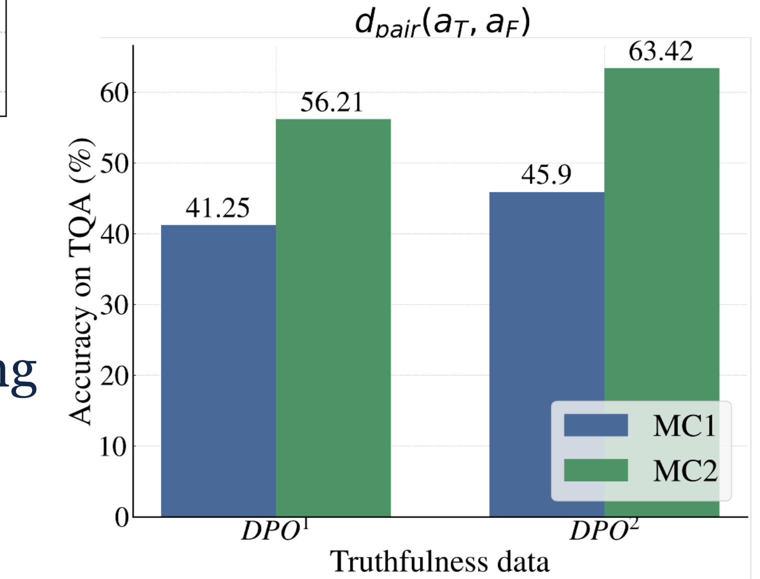
Interesting findings:

- The model learned by DPO is **more truthful** in the testing domain if there is a **smaller domain gap** between pairwise truthfulness training and testing data.
- The model learned via DPO is **more truthful** if the **distributional distance** between correct and incorrect answers within pairwise truthfulness data is **larger**.



A larger top-p value indicates a higher degree of transformation applied on training data, resulting in a larger domain gap between training and testing domains.





Training data used in the 2nd iteration of DPO shows larger pairwise distance between correct and incorrect answers, leading to a significant improvement in the truthfulness of the pretrained base model.