

# Can AI Assistants Know What They Don't Know?

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#### Abstract

Recently, AI assistants based on large language models (LLMs) show surprising performance in many tasks, such as dialogue, solving math problems, writing code, and using tools. Although LLMs possess intensive world knowledge, they still make factual errors when facing some knowledge intensive tasks, like open-domain question answering. These untruthful responses from the AI assistant may cause significant risks in practical applications. We believe that an AI assistant's refusal to answer questions it does not know is a crucial method for reducing hallucinations and making the assistant truthful. Therefore, in this paper, we ask the question "Can AI assistants know what they don't know and express them through natural language?" To answer this question, we construct a model-specific "I don't know" (Idk) dataset for an assistant, which contains its known and unknown questions, based on existing open-domain question answering datasets. Then we align the assistant with its corresponding Idk dataset and observe whether it can refuse to answer its unknown questions after alignment. Experimental results show that after alignment with Idk datasets, the assistant can refuse to answer most its unknown questions. For questions they attempt to answer, the accuracy is significantly higher than before the alignment.<sup>1</sup>

## 1 Introduction

Large language models (Brown et al., 2020; Chowdhery et al., 2023; Zeng et al., 2023; Touvron et al., 2023) possess extensive world knowledge and demonstrate capabilities in numerous natural language tasks that smaller models lack (Wei et al., 2022b). Recently, there are many artifical intelligence chat assistants built on large language models, capable of helping users accomplish various tasks in the daily life, providing a satisfactory user experience (Ouyang et al., 2022; OpenAI, 2022; Anthropic, 2023; Sun et al., 2023; Baichuan, 2023; Qwen-Team, 2023). Although these chat assistants can communicate frequently with users, they are prone to hallucinations (Shuster et al., 2021; Zhang et al., 2023b; Cheng et al., 2023), such as including factual errors in their generated responses (Wang et al., 2023b) or imitating human falsehoods in training corpus (Lin et al., 2022a), some of which are difficult for users to detect. These untruthful responses could potentially harm society and also diminish the credibility of AI assistants.

An AI assistant aligned with human values should be truthful (Evans et al., 2021), which means that it needs to provide accurate information consistent with the real world. When the assistant's output contains factual errors, it indicates that it may lack the corresponding knowledge internally, yet it fails to express the unknowns and refuse to give a answer.

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<sup>&</sup>lt;sup>1</sup>We will release our code, data and models at https://github.com/OpenMOSS/Say-I-Dont-Know.

	Unknowns	Knowns		
Known	Known Unknowns: Things the AI knows it doesn't know.	Known Knowns: Things the AI knows it knows.		
Unknown	Unknown Unknowns: Things the AI doesn't know it doesn't know.	Unknown Knowns: Things the AI doesn't know it knows.		

Figure 1: Knowledge quadrants of an AI assistant. "Unknowns" represents what the AI does not actually know. "Knowns" represents what the AI actually knows. "Known" represents what the AI believes it knows. "Unknown" represents what the AI believes it does not know.

However, a truthful AI assistant should be aware of what it knows and what it does not know, and be able to communicate this to the user. For questions that are known, the AI assistant should provide users with accurate information. For questions that are unknown, the AI assistant should avoid giving answers. Therefore, in this paper, we explore the question "Can AI assistants know what they don't know and express them through natural language?".

The AI assistant's perception of its own knowledge can be represented through knowledge quadrants (Yin et al., 2023b). The knowledge quadrant is a partition which can divide the knowledge into four categories: Known Knowns, Known Unknowns, Unknown Knowns and Unknown Unknowns, as shown in Figure 1. Known Knowns is crucial for a truthful AI assistant, as it relies on its own knowledge to provide accurate and reliable responses. The more knowledge that falls under the category of Known Knowns, the more helpful the AI assistant becomes. We use IK-IK (I know I know) to represent Known Knowns. Besides, we argue that a truthful AI assistant should also be aware of and express its lacks in certain knowledge. Specifically, it should admit when it doesn't have information on a topic or when the information is not certain to maintain truthfulness. This part of knowledge falls under the category of Known Unknowns. We use IK-IDK (I know I don't know) to represent Known Unknows. Unknown Unknowns and Unknown Knowns will cause untruthful and helpless generations. We use IDK-IDK (I don't know I don't know) and IDK-IK (I don't know I know) to represent Unknown Unknowns and Unknown Knowns respectively. To make AI assistants truthful, we need to teach AI assistants to know what they know and what they do not know to convert Unknown Knowns and Unknown Unknowns to Known Knowns and Known Unknowns.

Our approach is to align an AI assistant (like llama-2-7b-chat) with a model-specific **"I don't know" (Idk)** dataset which contains the assistant's known and unknown questions. We construct the Idk dataset based on an existing knowledge-intensive open-domain question answering dataset, TriviaQA (Joshi et al., 2017). We determine whether an assistant knows the answer to a question by evaluating its average accuracy across multiple responses to that question. Questions that the assistant answers incorrectly multiple times are marked as ones it does not know, and a template for refusal to answer is annotated. For questions that the assistant answers correctly multiple times, a correct answers it generates are used for the annotated answer. The assistant's accuracy threshold for being considered knowing the answer to a question is a hyperparameter, which we call **Ik threshold**. We discuss the details of constructing the Idk dataset in Section 3.1.

In order to teach AI assistants to know what they don't know, we conduct extensive experiments to exploit the most effective method, including prompting, supervised finetuning and preference-aware optimization. For prompting, we instruct the assistant to



Figure 2: Knowledge quadrants of AI assistants on the Idk dataset (Ik threshold=1.0). IK-IK represents the AI answers the questions correctly. IDK-IK represents the AI knows the answer but refuses to respond to the question. IDK-IDK represents the AI answers the question incorrectly. IK-IDK represents the AI doesn't know the answer and refuses to respond to the question. w/Idk-Prompting: Using prompting can transform certain IDK-IDK questions to IK-IDK questions. w/Idk-SFT: Idk-SFT allows the model to refuse to answer more questions it does not know, but it also tends to make the model more convervative, leading to incorrect refusals to answer some questions that it actually knows. w/Idk-DPO: Using preference-aware optimization, like DPO, can alleviate the model's excessive conservatism and reduce the number of IDK-IK questions.

refuse answering questions it does not know through a prompt. For supervised fine-tuning (SFT), we directly fine-tune the original assistant using our Idk datasets. For preferenceaware optimization, we use best-of-n sampling (BoN), proximal policy optimization (PPO) (Schulman et al., 2017; Ouyang et al., 2022), direct preference optimization (DPO) (Rafailov et al., 2023) and hindsight instruction relabeling (HIR) (Zhang et al., 2023a). We demonstrate some representative results in Figure 2.

The original model (llama-2-7b-chat) can be considered as lacking the ability to recognize questions it does not know<sup>2</sup>. It may guess an answer even it lacks the knowledge. As shown, there are many IDK-IDK questions, making the assistant untruthful. Instructing the model to refuse answering unknown questions through a prompt can be effective to some extent, but there are still numerous IDK-IK and IDK-IDK questions. After supervised fine-tuning

<sup>&</sup>lt;sup>2</sup>We conducted a search for keywords such as "I don't know", "not sure", "Sorry" in the responses of Llama-2-7b-chat and found that only a very small number of responses contained these keywords.

using Idk dataset, the number of IDK-IK and IDK-IDK has significantly decreased, indicating that the model's ability to be aware of its own knowledge has been enhanced. However, the model may also refuse to answer some questions it knows, leading to a decrease in the number of IK-IK questions. Compared to SFT model, preference-aware optimization (like DPO) can mitigate the phenomenon where the model incorrectly refuses to answer questions it knows. Besides, we conduct extensive ablation experiments to explore the effect of Ik threshold, data sources, model size and other settings.

Our findings can be summarized as follows:

- 1. After aligning using Idk datasets, AI assistants are capable of largely knowing what they know and what they do not know and refusing their unknown questions. Llama-2-7b-chat can definitively determine whether it knows the answer to up to **78.96**% of the questions in the test set. And it exhibits good performance on out-of-distribution test sets.
- 2. Supervised fine-tuning cause the model to become overly conservative, incorrectly rejecting known questions. Preference-aware optimization can mitigate this problem, promoting the overall proportion of IK-IK and IK-IDK questions.
- 3. The Ik threshold used to define knowns and unknowns questions influences the behavior of the assistant. The more questions labeled as "I don't know," the more likely the assistant is to refuse to answer questions. In general, the higher the Ik threshold, the greater the total number of Ik-Ik and Ik-Idk questions, resulting in a more truthful assistant.
- 4. Larger model is more adept at distinguishing which questions it knows and which it doesn't know. The use of Idk-SFT on Llama-2-70b-chat, as compared to Llama-2-7b-chat, results in a 5.8% improvement in the total number of IK-IK and IK-IDK questions.

# 2 Background

## 2.1 Aligning LLMs with Human Values

To build AI assistants based on large language models, we typically need to align these large language models with human values, making them helpful, truthful and harmless (Askell et al., 2021; Bai et al., 2022; Ouyang et al., 2022). Here we introduce several mainstream alignment methods related to our work. The most common alignment method for pretrained models is instruction tuning, also known as Supervised Fine-Tuning (SFT). Wei et al. (2022a); Sanh et al. (2022) fine-tune pre-trained models on a collection of NLP datasets combined with natural language instructions to enhance zero-shot performance on unseen tasks. Chung et al. (2022); Longpre et al. (2023) scale the number of tasks, the model size and fine-tune on mixed data. Sun et al. (2023) utilize Self-Instruct (Wang et al., 2023c) to synthesize three types of SFT data - helpful, honest, and harmless - and construct a conversational assistant. The step following SFT is preference optimization. Bai et al. (2022); Ouyang et al. (2022) use Reinforcement Learning from Human Feedback (RLHF) (Christiano et al., 2017; Stiennon et al., 2020). They first train a reward model on the human preference data and then optimize the policy model using Proximal Policy Optimization (PPO) (Schulman et al., 2017) with the trained reward model. Zhang et al. (2023a) propose a reward-free method named Hindsight Instruction Relabeling (HIR) to utilize preference data by converting feedback to instructions and training the model using supervised fine-tuning. Rafailov et al. (2023) propose Direct Preference Optimization (DPO) which can directly fine-tune language models to align with human preferences without the need of reward modeling.

## 2.2 Discovering LLMs' Knowledge

Large language models store extensive world knowledge during the pre-training. There has been increasing interest in researching knowledge in large language models. Kadavath et al. (2022); Lin et al. (2022b) fine-tune language models using a classification head or verbalized



Figure 3: **Top**: Construction process of the Idk dataset. **Bottom**: Construction process of preference pairs. The green response indicates a correct answer, the red response indicates an incorrect answer, and "I don't know" represents the template for refusal to answer.

confidence. However, they don't teach models to aware their knowledge boundary and refuse to answer the questions they don't know. Yin et al. (2023b) propose the SelfAware dataset to evaluate the ability of LLMs to recognize what they don't know, finding that there is still an apparent gap compared to human. Burns et al. (2023) propose an unsupervised method to find latent knowledge inside the activations of a language model by answering yes-no questions given only unlabeled model activations. Ren et al. (2023) investigate whether LLMs can perceive their knowledge boundaries or not under retrieval-augmented setting and normal setting. Zhao et al. (2023); Manakul et al. (2023); Anonymous (2023) check the generated answers in an unsupervised way to judge whether the model knows the question. The basic idea is that if the model knows the answer to a question, then the diversity of multiple sampling generations should be relatively low.

## 2.3 Mitigating LLMs' Factual Errors

There are some studies focused on eliminating factual errors in AI assistants. Asai et al. (2023) propose a framework named SELF-RAG to enhance an LM's factuality by retrieval augmentation and self-reflection. Li et al. (2023) first find truthful directions through probing and then do inference-time intervention in these truthful directions. Zou et al. (2023) use representation engineering to enhance factuality of the model's output. Chuang et al. (2023) propose a simple decoding strategy for reducing hallucinations by contrasting the differences in tokens' logits obtained from different layers. Tian et al. (2023) directly fine-tune language models to learn factuality from preference dataset using direct preference optimization. However, there is currently no method that can guarantee the complete elimination of factual errors. In practical applications, it is a necessary feature for AI assistants to refuse to answer questions they do not know.

# 3 Methodology

## 3.1 Construction of the Idk Dataset

Given a knowledge-intensive question answering dataset, it is hard to precisely determine which questions the model truly knows the answers to, which due to the model having varying degrees of confidence for different knowledge. Therefore, following the approach of previous work (Kadavath et al., 2022; Lin et al., 2022b), we sample multiple responses from the model for each question, calculating the accuracy rate across these responses as a measure of the model's confidence regarding that question. Finally, we select a specific level of confidence as the criterion for determining whether the model knows or does not know the answer to a question, that is the Ik threshold. To construct the QA pairs in the Idk dataset, for questions that the model does not know, we use a template for refusal to reply as the answer. For questions that the model knows, we select a correct response generated by the model itself as the answer. The procedure is demonstrated in Figure 3 (top). Our refusal to answer template is:

This question is beyond the scope of my knowledge, and I am not sure what the answer is.

We use "I don't know" and the Idk template to refer to this template in the following paper.

**Determine whether the output of a model is correct.** In order to construct the Idk dataset, we need an automatic method to evaluate whether the model's outputs are correct. According to the experimental results presented in Wang et al. (2023a), employing lexical matching, which checks whether the golden answers appear in the responses generated by the model, to evaluate on a subset of the TriviaQA's validation set (Joshi et al., 2017) yields a consistency rate of approximately 90% with human evaluations. We consider lexical matching to be a relatively accurate automatic evaluation method for the TriviaQA dataset. Besides, TriviaQA is a mainstream knowledge-intensive open-domain question answering dataset. Therefore, we construct our Idk dataset based on the TriviaQA dataset.

**Meaning of different Ik thresholds.** The model is required to refuse to answer questions where the confidence level is below the Ik threshold. It is important to note that different Ik thresholds will result in different Idk datasets. A high Ik threshold indicates that the model will only answer a question if it possesses a high level of confidence. Conversely, if the Ik threshold is low, the model will answer questions with a lower level of confidence required. In other words, a high Ik threshold represents a conservative response strategy, whereas a low Ik threshold represents a more aggressive response strategy. In this work, we sampled ten responses for each question and derived ten discrete Ik thresholds based on varying accuracy rates. For the sake of simplicity, we set the Ik threshold to 1.0, meaning that the model is considered to know the answer to the question only if all ten of its responses are correct. Unless specifically stated otherwise, the Idk dataset mentioned hereafter is constructed based on an Ik threshold of 1.0. We discuss the impact of different Ik thresholds in Section 4.

In the following sections, we introduce our methods to teach AI assistants to say "I don't know" when encounter unknown questions. Since the AI assistant we discuss is based on large language models, we will interchangeably use the terms "model" and "assistant" in the following sections.

## 3.2 Idk Prompting

For models capable of following human instructions, such as Llama-2-7b-chat, We can directly instruct an assistant to say "I don't know" to unknown questions by adding a prompt in front of the input question. We call this method Idk-Prompting. This requires the model to have a high capability for following instructions, but the advantage is that it eliminates the need for additional training. We call such a prompt an Idk prompt. Our Idk prompt is as follows:

Answer the following question, and if you don't know the answer, only reply with "I don't know": <Question>

As for pre-trained models lacking the ability to follow instructions, Idk-Prompting may not yield satisfactory results.

#### 3.3 Idk Supevised Fine-tuning

Supervised Fine-tuing is a simple yet effective alignment method. We directly use the Idk dataset for Supervised Fine-tuning of the model. Since the Idk dataset contains both questions and responses, this constitutes a conditional generation task. We input the questions into the model and require the model to predict the responses. We perform the standard sequence-to-sequence loss to train our model. SFT details are demonstrated in Appendix B.1.

#### 3.4 Preference-aware Optimization

In this section, we introduce how we conduct preference-aware optimization to help the model perceive its internal knowledge better.

**Direct Preference Optimization (DPO)** To conduct DPO, we first train a SFT model on half of the Idk dataset as a warm up, then we collect responses from this SFT model on the other half of the Idk data. For a given question, we conduct random sampling to gather multiple responses. Finally, we construct preference data based on the these generated responses. We demonstrate the procedure in Figure 3 (bottom). A preference data sample consists of a question, a chosen response, and a rejected response. The questions in the Idk dataset can be categorized into two types: those the model knows and those it does not know. For questions the model knows, we use the correct response generated by it as the chosen response and "I don't know" as the rejected response. For questions the model does not know, we use "I don't know" as the chosen response and its incorrectly generated response as the rejected response. Besides, we find that only using the DPO loss Rafailov et al. (2023) can occasionally result in the model's inability to accurately generate the Idk template. Therefore, in addition to the original DPO loss, we also incorporate SFT loss for the chosen responses and multiply it by a coefficient  $\alpha$ . The details of the DPO are demonstrated in Appendix B.2.

**Best-of-n Sampling (BoN)** We also try to determine if the model knows the answer to a certain question by training a reward model to score the candidate responses. We first train a SFT model using a half of the Idk data and then use the SFT model to initialize the reward model. After collecting responses on the other half of the Idk dataset and constructing preference data using the same procedure as 3, we train the reward model using a pairwise loss. During inference, we employ the Best-of-10 strategy. First, we sample ten responses using the SFT model, then we score these candidate responses with the reward model. The response with the highest reward score is selected as the final response. The details of reward modeling are demonstrated in Appendix B.3.

**Proximal Policy Optimization (PPO)** Based on our reward model, we can use proximal policy optimization to optimize the model. We use the same inputs for PPO training as we do for reward modeling, but sample responses in an online manner. The details of the PPO are demonstrated in Appendix B.4.

**Hindsight Instruction Relabeling (HIR)** So far, our Idk dataset is constructed based on a fixed Ik threshold. In order to utilize all Idk datasets constructed with different Ik thresholds, inspired by Hindsight Instruction Relabeling (Zhang et al., 2023a), we design an instruction format to relabel all Idk datasets. Specifically, we prepend the following instruction to each question in the Idk datasets:

Your current knowledge expression confidence level is <X>, please answer the user's question: <Question>

where < *Question* > is a question from an Idk dataset and < X > is the value of model's knowledge confidence level ranging from 0 to 1.0, derived from the Ik threshold corre-

sponding to the Idk dataset. The lower the knowledge confidence level, the more inclined the model is to refuse answering questions. Then we use the combined Idk dataset to perform supervised fine-tuning. The advantage of using instruction relabeling is that we can control the model to adopt either a conservative or aggressive response strategy through the instruction, without the need to retrain the model. The details of HIR are demonstrated in Appendix B.5.

# 4 Experiments

## 4.1 Dataset

TriviaQA (Joshi et al., 2017) is a reading comprehension dataset, but its question-answer pairs can be used for open-domain question answering tasks. We use the training set of TriviaQA, consisting of 87,622 samples, to construct the training and development sets of the Idk dataset. Since TriviaQA does not provide ground truth for the test set, we use the development set of TriviaQA to construct the test set for the Idk dataset, which comprises a total of 11,313 samples. The detailed statistical information of the Idk datasets is provided in Appendix A.

Additionally, we use the Natural Questions (NQ) (Kwiatkowski et al., 2019) and ALCUNA (Yin et al., 2023a) datasets as the out-of-distribution (OOD) questions. NQ is a question answering dataset consisting of real queries issued to the Google search engine. We use the development set of NQ-Open, which contains 3,610 samples, to construct the OOD test set. According to the experimental results in Wang et al. (2023a), using lexical matching for the automatic evaluation on the development set of the NQ dataset shows more than 80% consistency with human expert assessments. Therefore, we use lexical matching to judge the correctness of model answers and to label "I don't know" responses.

ALCUNA is a benchmark to assess LLMs' abilities in new knowledge understanding. It creates new artificial entities by altering existing entity attributes and generates questions about these artificial entities. Since these entities are artificially created, the model cannot possibly possess this knowledge. Therefore, we use a portion of the questions from ALCUNA to test whether the model can refuse to answer, totaling 8,857 samples.

## 4.2 Metrics and Evaluation

We report the following metrics.

- IK-IK Rate: I know what I know (Ik-Ik) rate represents the proportion of questions answered correctly by the model out of all questions.
- IK-IDK Rate: I know what I don't know (Ik-Idk) rate represents the proportion of questions that the model correctly refuses to answer, out of all questions.
- TRUTHFUL Rate: Truthful rate is the sum of Ik-Ik rate and Ik-Idk rate. It represents the proportion of questions for which the model provides truthful responses. The higher the value of TRUTHFUL rate, the clearer the model's perception of what it knows and does not know, which also indicates a higher level of truthfulness. The TRUTHFUL value of an ideal truthful model should ideally reach 100%.

The higher these three metrics are, the better. Among these metrics, we argue that the TRUTHFUL rate is the most important one because it indicates the probability that users will receive a truthful response.

To calculate these metrics, we categorize the inference results into four knowledge quadrants using the following method.

• IK-IK: If a question model does not refuse to answer and the answer is correct, then the question belongs to the Ik-Ik category. We determine whether the model's answer is correct by checking if the ground truth appears in the model's response.

- IK-IDK: If a question model refuses to answer, and the question is marked as one that the model does not know, then this question belongs to Ik-Idk category. We determine whether the model refuses to answer a question by checking whether the refusal template appears in the model's response.
- IDK-IK: If a question model refuses to answer, but the question is not marked as one the model does not know, then this question falls into the Idk-Ik category.
- IDK-IDK: If a question model does not refuse to answer but provides an incorrect response, then the question belongs to the Idk-Idk category.

We use Llama-2-7b-chat as our initial model for further training, with specific training details introduced in Appendix B. We test the trained model on the test set of the Idk dataset to evaluate whether the model can distinguish between questions it knows and does not know. Except for Idk-BoN, we use greedy decoding in all tests. For Idk-BoN, we set the temperature coefficient to 1.0 and top\_p to 0.9, sample ten responses, and then score them using the reward model. The response with the highest reward score is selected as the final model response.

	TriviaQA		Natural Questions			ALCUNA	
	Ік-Ік	Ik-Idk	Truthful	Ік-Ік	Ik <b>-</b> Idk	Truthful	IK-IDK
Idk-Dataset <sub>test</sub>	45.05	54.95	100.00	24.65	75.35	100.00	100.00
Idk-Prompting	37.36	29.58	66.93	19.75	41.72	61.47	91.67
Idk-SFT	28.57	46.19	$74.75_{\uparrow 7.82}$	15.93	53.99	$69.92_{\uparrow 8.45}$	98.01
Idk-DPO	39.30	38.59	$77.89_{\uparrow 10.96}$	20.91	45.60	$66.51_{15.04}$	98.08
Idk-BoN <sub><math>N=10</math></sub>	38.37	40.59	<b>78.96</b> ↑12.03	20.55	47.40	$67.95_{\uparrow 6.48}$	98.32
Idk-PPO	35.90	40.57	$76.47_{19.54}$	23.13	42.08	$65.21_{\uparrow 3.47}$	92.66
Idk-HIR	27.36	48.55	$75.91_{\uparrow 8.98}$	15.40	56.90	<b>72.30</b> ↑10.83	98.96

#### 4.3 Main Results

Table 1: Overall results on the test set of the Idk dataset constructed based on TriviaQA and out-of-distribution test sets.

The overall results are in Table 1. The Idk-Dataset used for evaluation contains 45.05% IK-IK questions and 54.95% IK-IDK questions, which can be seen as two upper bounds of IK-IK and IK-IDK rate. Simply using an Idk prompt to let the model refuse to answer questions it doesn't know can have a certain effect, but the model's TRUTHFUL rate is still only 66.93%. The Idk-SFT can increase the TRUTHFUL rate ti 74.75%, but this will result in a decrease in the IK-IK rate, which can be considered a form of "alignment tax". We find that preference optimization can encourage the model to answer questions, thereby mitigating the alignment tax. DPO<sup>3</sup>, PPO, and BoN can all reduce the loss of IK-IK while maintaining a relatively high IK-IDK rate. Idk-BoN achieves the highest TRUTHFUL rate. Idk-HIR combines all Idk datasets, which can improve IK-IDK rate but help less for IK-IK rate. However, Idk-HIR provides an switching method for Ik-threshold that does not need to retrain the model. Overall, by aligning with the Idk dataset, we can transform IDK-IK and IDK-IDK questions into IK-IK and IK-IDK questions. The model can have a clear perception of whether it knows the answers to most questions in the test set, significantly increasing truthfulness compared to before the alignment. The additional experimental results are represented in Appendix C.

**Evaluation on out-of-distribution data** We also test whether the aligned model is capable of refusing to answer questions it does not know when encountering out-of-distribution (OOD) data. We first construct the Idk dataset for testing based on Natural Questions, setting the Ik threshold to 1.0. As shown in Tabel 1, the Idk dataset contains 24.65% IK-IK

<sup>&</sup>lt;sup>3</sup>We find that the DPO model, when refusing to answer questions within ALCUNA, occasionally rephrases our Idk template. Consequently, we utilize a substring of the original Idk template: "I am not sure what the answer is" to detect whether the model refuse to answer the question.

questions and 75.35% IK-IDK questions, which means Natural Questions is more challenging than TriviaQA. The results on Natural Questions are similar to those on TriviaQA. The algined models show improvements in all metrics compared to using prompts. In contrast to the results on TriviaQA, Idk-HIR achieves the highest TRUTHFUL rate, rather than Idk-BoN. Furthermore, the models aligned using preference optimization methods exhibit a reduction in the TRUTHFUL rate compared to the Idk-SFT. We believe this is due to the fact that preference optimization encourages the model to answer more questions. We can observe that, compared to the Idk-SFT model, preference-optimized models have more IK-IK questions but less IK-IDK questions. In addition to this, we utilize ALCUNA to construct the Idk dataset, which only contains ID-IDK questions. The results from Table 1 indicate that the prompting method can already enable the model to refuse answering most unanswerable questions. After alignment, the model achieves an even higher IK-IDK rate. The model aligned with TriviaQA demonstrates a high TRUTHFUL rate on Natural Questions and a high IK-IDK rate on ALCUNA, suggesting that the model's behavior of refusing to answer unknown questions can be generalized to OOD data.

#### 4.4 Ablation Study

	Ік-Ік↑	Ik-Idk†	Idk-Ik↓	Idk-Idk↓	Truthful↑
Idk-SFT <sub>7b</sub>	28.57	46.19	19.24	6.00	74.75
w/Llama-2-13b-chat w/Llama-2-70b-chat	33.92 57.78	41.43 22.68	17.45 10.78	7.20 8.66	$75.35_{\uparrow 0.60}\ 80.55_{\uparrow 5.8}$
w/Idk-Mistral w/Idk-Baichuan	18.35 8.85	50.65 53.07	27.68 36.37	3.31 1.71	$\begin{array}{c} 69.00_{\downarrow 5.75} \\ 61.92_{\downarrow 12.83} \end{array}$

In this section, we analyze which factors affect the model's ability to recognize questions it does not know through extensive abliation experiments.

**Effect of model size** The capabilities of LLMs are often closely related to the number of their parameters: models with a larger size tend to be more powerful. We conduct Idk-SFT on Llama-2-7b-chat, Llama-2-13b-chat and Llama-2-70b-chat to observe whether the size of the model affects the effectiveness of Idk-SFT. In Table 2, we report the proportions of each knowledge quadrant for models of different sizes. However, the label distribution of the Idk dataset corresponding to different initial models is inconsistent (the larger the model, the more IK-IK questions), as shown in Appendix A.3. This results in the IK-IK rate and IK-IDK rate being incomparable. Therefore, we mainly focus on the TRUTHFUL rate of different models. The TRUTHFUL rate of the 13B model is slightly higher than that of the 7B model. The TRUTHFUL rate of the 70B model is significantly higher than that of the 13B and 7B models. This indicates that larger models are more adpet at distinguishing between questions they know and do not know.

**Effect of data sources** Due to the differences in the pre-training process, different pretrained models possess distinct knowledge. During training, we construct model-specific Idk dataset for different pre-trained models. This is because we want the model to determine whether it knows the answer to a question based on its internal knowledge, rather than learning to recognize some specific patterns of questions. The model-specific Idk dataset can connect the model's internal knowledge with the labels of the Idk dataset. To explore the impact of using a non-model-specific Idk dataset on training, we construct two Idk training sets using Mistral-7B-Instruct-v0.1 (Jiang et al., 2023) and Baichuan2-7B-chat (Baichuan, 2023) respectively, named "Idk-Mistral" and "Idk-Baichuan". We present label distributions of these Idk datasets in Appendix A.3 As shown in Tabel 2, using non-model-specific Idk datasets like "Idk-Mistral" or "Idk-Baichuan" does result in a TRUTHFUL rate loss. Due to the numerous Idk questions in the Idk-Mistral and Idk-Baichuan datasets, the trained model tends to be more inclined towards refusing to answer questions, which has resulted



Figure 4: Left: Variation in the proportions of Ik and Idk questions within the Idk datasets constructed based on different Ik thresholds. **Right:** The changes in IK-IK rate, IK-IDK rate, and TRUTHFUL rate after conducting Idk-SFT with different Idk datasets.

in a significant reduction in Ik-Ik related queries, far below their proportion in the dataset. This indicates that constructing a model-specific Idk dataset is necessary for enabling the model to learn to refuse to answer questions it does not know.

Effect of IK threshold So far, we have fixed the Ik threshold to 1.0. Here, we discuss the impact of different Ik thresholds on model behaviors. The Ik threshold primarily affects the distribution of labels in the Idk dataset, with a higher Ik threshold indicating that more questions will be labeled as "I don't know". As demonstrated in Figure 4 (left), the higher the value of the Ik threshold, the greater the proportion of Idk questions. This is because when the Ik threshold is high, only questions with a high confidence level will be annotated as questions known to the model. As shown in Figure 4 (right), increasing the Ik threshold results in a decrease in the IK-IK rate and an increase in the IK-IDK rate. As the Ik threshold is raised, the model's TRUTHFUL rate will continue to improve. In other words, setting a high Ik threshold aids the model in better distinguish between knowledge it knows and does not know, making the model more truthful. In contrast, setting a low Ik threshold can make the model more helpful, since the number of IK-IK questions will increase. Besides, we find that as the proportion of Idk questions in the dataset increases, the model tends to refuse to answer questions more frequently. We report the F1 scores of Idk and Ik questions in different Idk datasets in Appendix C.2 and the knowledge quadrants under different Ik thresholds in C.1.

## 5 Conclusion

In this paper, we explore the question "Can AI assistants know what they don't know?". We find that after aligning the AI assistant with its own Idk("I don't know") dataset which contains its known and unknown questions, the assistant can be aware of what it does not know to a certain extent. In the given test set for open-domain question-answering, Llama-2-7b-chat can explicitly indicate whether it knows or does not know the answers to up to 78.96% of the questions and refuse to answer the questions it does not know. To achieve this, we utilize various methods to use the Idk dataset for alignment, including prompting, supervised fine-tuning and preference-aware optimization. We also find that the Ik threshold influences the model's tendency to decline responses. Empolying an Idk dataset from different models for alignment results in a performance degradation. Furthermore, a large model like Llama-2-70b-chat achieves a higher TRUTHFUL rate. An AI assistant's refusal to answer questions beyond its knowledge can reduce hallucinations. We believe this is an essential behavior for a truthful AI assistant.

#### References

- Anonymous. INSIDE: LLMs' internal states retain the power of hallucination detection. In *Submitted to The Twelfth International Conference on Learning Representations*, 2023. URL https://openreview.net/forum?id=Zj12nzlQbz. under review.
- Anthropic. Introducing claude, 2023. URL https://www.anthropic.com/index/ introducing-claude.
- Akari Asai, Zeqiu Wu, Yizhong Wang, Avirup Sil, and Hannaneh Hajishirzi. Self-rag: Learning to retrieve, generate, and critique through self-reflection. *CoRR*, abs/2310.11511, 2023. doi: 10.48550/ARXIV.2310.11511. URL https://doi.org/10.48550/arXiv.2310. 11511.
- Amanda Askell, Yuntao Bai, Anna Chen, Dawn Drain, Deep Ganguli, Tom Henighan, Andy Jones, Nicholas Joseph, Benjamin Mann, Nova DasSarma, Nelson Elhage, Zac Hatfield-Dodds, Danny Hernandez, Jackson Kernion, Kamal Ndousse, Catherine Olsson, Dario Amodei, Tom B. Brown, Jack Clark, Sam McCandlish, Chris Olah, and Jared Kaplan. A general language assistant as a laboratory for alignment. *CoRR*, abs/2112.00861, 2021. URL https://arxiv.org/abs/2112.00861.
- Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, Nicholas Joseph, Saurav Kadavath, Jackson Kernion, Tom Conerly, Sheer El Showk, Nelson Elhage, Zac Hatfield-Dodds, Danny Hernandez, Tristan Hume, Scott Johnston, Shauna Kravec, Liane Lovitt, Neel Nanda, Catherine Olsson, Dario Amodei, Tom B. Brown, Jack Clark, Sam McCandlish, Chris Olah, Benjamin Mann, and Jared Kaplan. Training a helpful and harmless assistant with reinforcement learning from human feedback. *CoRR*, abs/2204.05862, 2022. doi: 10.48550/ARXIV.2204.05862. URL https://doi.org/10.48550/arXiv.2204.05862.
- Baichuan. Baichuan 2: Open large-scale language models. *arXiv preprint arXiv:2309.10305*, 2023. URL https://arxiv.org/abs/2309.10305.
- Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In Hugo Larochelle, Marc'Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin (eds.), Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual, 2020. URL https://proceedings.neurips.cc/paper/2020/hash/ 1457c0d6bfcb4967418bfb8ac142f64a-Abstract.html.
- Collin Burns, Haotian Ye, Dan Klein, and Jacob Steinhardt. Discovering latent knowledge in language models without supervision. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/pdf?id=ETKGubyOhcs.
- Qinyuan Cheng, Tianxiang Sun, Wenwei Zhang, Siyin Wang, Xiangyang Liu, Mozhi Zhang, Junliang He, Mianqiu Huang, Zhangyue Yin, Kai Chen, and Xipeng Qiu. Evaluating hallucinations in chinese large language models. *CoRR*, abs/2310.03368, 2023. doi: 10.48550/ARXIV.2310.03368. URL https://doi.org/10.48550/arXiv.2310.03368.
- Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny

Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. Palm: Scaling language modeling with pathways. *J. Mach. Learn. Res.*, 24:240:1–240:113, 2023. URL http://jmlr.org/papers/v24/22-1144.html.

- Paul F. Christiano, Jan Leike, Tom B. Brown, Miljan Martic, Shane Legg, and Dario Amodei. Deep reinforcement learning from human preferences. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett (eds.), Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA, pp. 4299–4307, 2017. URL https://proceedings.neurips.cc/paper/2017/hash/ d5e2c0adad503c91f91df240d0cd4e49-Abstract.html.
- Yung-Sung Chuang, Yujia Xie, Hongyin Luo, Yoon Kim, James R. Glass, and Pengcheng He. Dola: Decoding by contrasting layers improves factuality in large language models. *CoRR*, abs/2309.03883, 2023. doi: 10.48550/ARXIV.2309.03883. URL https://doi.org/ 10.48550/arXiv.2309.03883.
- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Sharan Narang, Gaurav Mishra, Adams Yu, Vincent Y. Zhao, Yanping Huang, Andrew M. Dai, Hongkun Yu, Slav Petrov, Ed H. Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. Scaling instruction-finetuned language models. *CoRR*, abs/2210.11416, 2022. doi: 10.48550/ARXIV.2210.11416. URL https://doi.org/10.48550/arXiv.2210. 11416.
- Owain Evans, Owen Cotton-Barratt, Lukas Finnveden, Adam Bales, Avital Balwit, Peter Wills, Luca Righetti, and William Saunders. Truthful AI: developing and governing AI that does not lie. *CoRR*, abs/2110.06674, 2021. URL https://arxiv.org/abs/2110.06674.
- Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de Las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. Mistral 7b. *CoRR*, abs/2310.06825, 2023. doi: 10.48550/ARXIV.2310.06825. URL https://doi.org/ 10.48550/arXiv.2310.06825.
- Mandar Joshi, Eunsol Choi, Daniel S. Weld, and Luke Zettlemoyer. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. In Regina Barzilay and Min-Yen Kan (eds.), *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 August 4, Volume 1: Long Papers*, pp. 1601–1611. Association for Computational Linguistics, 2017. doi: 10.18653/V1/P17-1147. URL https://doi.org/10.18653/v1/P17-1147.
- Saurav Kadavath, Tom Conerly, Amanda Askell, Tom Henighan, Dawn Drain, Ethan Perez, Nicholas Schiefer, Zac Hatfield-Dodds, Nova DasSarma, Eli Tran-Johnson, Scott Johnston, Sheer El Showk, Andy Jones, Nelson Elhage, Tristan Hume, Anna Chen, Yuntao Bai, Sam Bowman, Stanislav Fort, Deep Ganguli, Danny Hernandez, Josh Jacobson, Jackson Kernion, Shauna Kravec, Liane Lovitt, Kamal Ndousse, Catherine Olsson, Sam Ringer, Dario Amodei, Tom Brown, Jack Clark, Nicholas Joseph, Ben Mann, Sam McCandlish, Chris Olah, and Jared Kaplan. Language models (mostly) know what they know. *CoRR*, abs/2207.05221, 2022. doi: 10.48550/ARXIV.2207.05221. URL https://doi.org/10. 48550/arXiv.2207.05221.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur P. Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina

Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. Natural questions: a benchmark for question answering research. *Trans. Assoc. Comput. Linguistics*, 7:452–466, 2019. doi: 10.1162/TACL\\_A\\_00276. URL https://doi.org/10.1162/tacl\_a\_00276.

- Kenneth Li, Oam Patel, Fernanda B. Viégas, Hanspeter Pfister, and Martin Wattenberg. Inference-time intervention: Eliciting truthful answers from a language model. *CoRR*, abs/2306.03341, 2023. doi: 10.48550/ARXIV.2306.03341. URL https://doi.org/10. 48550/arXiv.2306.03341.
- Stephanie Lin, Jacob Hilton, and Owain Evans. Truthfulqa: Measuring how models mimic human falsehoods. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (eds.), *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022*, pp. 3214–3252. Association for Computational Linguistics, 2022a. doi: 10.18653/v1/2022.acl-long.229. URL https://doi.org/10.18653/v1/2022.acl-long.229.
- Stephanie Lin, Jacob Hilton, and Owain Evans. Teaching models to express their uncertainty in words. *Trans. Mach. Learn. Res.*, 2022, 2022b. URL https://openreview.net/forum? id=8s8K2UZGTZ.
- Shayne Longpre, Le Hou, Tu Vu, Albert Webson, Hyung Won Chung, Yi Tay, Denny Zhou, Quoc V. Le, Barret Zoph, Jason Wei, and Adam Roberts. The flan collection: Designing data and methods for effective instruction tuning, 2023.
- Potsawee Manakul, Adian Liusie, and Mark J. F. Gales. Selfcheckgpt: Zero-resource blackbox hallucination detection for generative large language models. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023, Singapore, December 6-10, 2023*, pp. 9004–9017. Association for Computational Linguistics, 2023. URL https://aclanthology.org/2023. emnlp-main.557.

OpenAI. Introducing chatgpt, 2022. URL https://openai.com/blog/chatgpt.

- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F. Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback. In *NeurIPS*, 2022. URL http://papers.nips.cc/paper\_files/ paper/2022/hash/b1efde53be364a73914f58805a001731-Abstract-Conference.html.
- Qwen-Team. Qwen technical report. 2023. URL https://qianwen-res.oss-cn-beijing. aliyuncs.com/QWEN\_TECHNICAL\_REPORT.pdf.
- Rafael Rafailov, Archit Sharma, Eric Mitchell, Stefano Ermon, Christopher D. Manning, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. *CoRR*, abs/2305.18290, 2023. doi: 10.48550/ARXIV.2305.18290. URL https://doi.org/10.48550/arXiv.2305.18290.
- Ruiyang Ren, Yuhao Wang, Yingqi Qu, Wayne Xin Zhao, Jing Liu, Hao Tian, Hua Wu, Ji-Rong Wen, and Haifeng Wang. Investigating the factual knowledge boundary of large language models with retrieval augmentation. *CoRR*, abs/2307.11019, 2023. doi: 10.48550/ARXIV.2307.11019. URL https://doi.org/10.48550/arXiv.2307.11019.
- Victor Sanh, Albert Webson, Colin Raffel, Stephen H. Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal V. Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Févry, Jason Alan Fries, Ryan Teehan, Teven Le Scao, Stella Biderman, Leo Gao, Thomas Wolf, and Alexander M. Rush. Multitask prompted training enables zero-shot task generalization. In *The*

Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022. OpenReview.net, 2022. URL https://openreview.net/forum?id=9Vrb9D0WI4.

- John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *CoRR*, abs/1707.06347, 2017. URL http://arxiv.org/abs/1707.06347.
- Kurt Shuster, Spencer Poff, Moya Chen, Douwe Kiela, and Jason Weston. Retrieval augmentation reduces hallucination in conversation. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 16-20 November, 2021,* pp. 3784–3803. Association for Computational Linguistics, 2021. doi: 10.18653/v1/2021. findings-emnlp.320. URL https://doi.org/10.18653/v1/2021.findings-emnlp.320.
- Nisan Stiennon, Long Ouyang, Jeff Wu, Daniel M. Ziegler, Ryan Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul F. Christiano. Learning to summarize from human feedback. *CoRR*, abs/2009.01325, 2020. URL https://arxiv.org/abs/2009.01325.
- Tianxiang Sun, Xiaotian Zhang, Zhengfu He, Peng Li, Qinyuan Cheng, Hang Yan, Xiangyang Liu, Yunfan Shao, Qiong Tang, Xingjian Zhao, Ke Chen, Yining Zheng, Zhejian Zhou, Ruixiao Li, Jun Zhan, Yunhua Zhou, Linyang Li, Xiaogui Yang, Lingling Wu, Zhangyue Yin, Xuanjing Huang, and Xipeng Qiu. Moss: Training conversational language models from synthetic data. 2023.
- Katherine Tian, Eric Mitchell, Huaxiu Yao, Christopher D. Manning, and Chelsea Finn. Fine-tuning language models for factuality. *CoRR*, abs/2311.08401, 2023. doi: 10.48550/ ARXIV.2311.08401. URL https://doi.org/10.48550/arXiv.2311.08401.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurélien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models. *CoRR*, abs/2302.13971, 2023. doi: 10.48550/arXiv. 2302.13971. URL https://doi.org/10.48550/arXiv.2302.13971.
- Cunxiang Wang, Sirui Cheng, Qipeng Guo, Zhikun Xu, Bowen Ding, Yidong Wang, Xiangkun Hu, Zheng Zhang, and Yue Zhang. Evaluating open-qa evaluation, 2023a. URL https://arxiv.org/abs/2305.12421.
- Cunxiang Wang, Xiaoze Liu, Yuanhao Yue, Xiangru Tang, Tianhang Zhang, Jiayang Cheng, Yunzhi Yao, Wenyang Gao, Xuming Hu, Zehan Qi, Yidong Wang, Linyi Yang, Jindong Wang, Xing Xie, Zheng Zhang, and Yue Zhang. Survey on factuality in large language models: Knowledge, retrieval and domain-specificity. *CoRR*, abs/2310.07521, 2023b. doi: 10.48550/ARXIV.2310.07521. URL https://doi.org/10.48550/arXiv.2310.07521.
- Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language models with self-generated instructions. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki (eds.), Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023, pp. 13484–13508. Association for Computational Linguistics, 2023c. doi: 10.18653/V1/2023.ACL-LONG.754. URL https://doi.org/10.18653/v1/2023.acl-long.754.
- Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. Finetuned language models are zero-shot learners. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net, 2022a. URL https://openreview.net/forum?id=gEZrGCozdqR.
- Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. Emergent abilities of large language models. *Trans. Mach. Learn. Res.*, 2022, 2022b. URL https: //openreview.net/forum?id=yzkSU5zdwD.

- Xunjian Yin, Baizhou Huang, and Xiaojun Wan. ALCUNA: large language models meet new knowledge. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023, Singapore, December 6-10, 2023, pp. 1397–1414. Association for Computational Linguistics, 2023a. URL https://aclanthology.org/2023.emnlp-main.87.
- Zhangyue Yin, Qiushi Sun, Qipeng Guo, Jiawen Wu, Xipeng Qiu, and Xuanjing Huang. Do large language models know what they don't know? In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki (eds.), *Findings of the Association for Computational Linguistics: ACL 2023, Toronto, Canada, July 9-14, 2023, pp. 8653–8665.* Association for Computational Linguistics, 2023b. doi: 10.18653/v1/2023.findings-acl.551. URL https: //doi.org/10.18653/v1/2023.findings-acl.551.
- Aohan Zeng, Xiao Liu, Zhengxiao Du, Zihan Wang, Hanyu Lai, Ming Ding, Zhuoyi Yang, Yifan Xu, Wendi Zheng, Xiao Xia, Weng Lam Tam, Zixuan Ma, Yufei Xue, Jidong Zhai, Wenguang Chen, Zhiyuan Liu, Peng Zhang, Yuxiao Dong, and Jie Tang. GLM-130B: an open bilingual pre-trained model. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/pdf?id=-Aw0rrrPUF.
- Tianjun Zhang, Fangchen Liu, Justin Wong, Pieter Abbeel, and Joseph E. Gonzalez. The wisdom of hindsight makes language models better instruction followers. In Andreas Krause, Emma Brunskill, Kyunghyun Cho, Barbara Engelhardt, Sivan Sabato, and Jonathan Scarlett (eds.), *International Conference on Machine Learning, ICML 2023, 23-29 July 2023, Honolulu, Hawaii, USA*, volume 202 of *Proceedings of Machine Learning Research*, pp. 41414– 41428. PMLR, 2023a. URL https://proceedings.mlr.press/v202/zhang23ab.html.
- Yue Zhang, Yafu Li, Leyang Cui, Deng Cai, Lemao Liu, Tingchen Fu, Xinting Huang, Enbo Zhao, Yu Zhang, Yulong Chen, Longyue Wang, Anh Tuan Luu, Wei Bi, Freda Shi, and Shuming Shi. Siren's song in the AI ocean: A survey on hallucination in large language models. *CoRR*, abs/2309.01219, 2023b. doi: 10.48550/ARXIV.2309.01219. URL https://doi.org/10.48550/arXiv.2309.01219.
- Yukun Zhao, Lingyong Yan, Weiwei Sun, Guoliang Xing, Chong Meng, Shuaiqiang Wang, Zhicong Cheng, Zhaochun Ren, and Dawei Yin. Knowing what llms DO NOT know: A simple yet effective self-detection method. *CoRR*, abs/2310.17918, 2023. doi: 10.48550/ ARXIV.2310.17918. URL https://doi.org/10.48550/arXiv.2310.17918.
- Andy Zou, Long Phan, Sarah Chen, James Campbell, Phillip Guo, Richard Ren, Alexander Pan, Xuwang Yin, Mantas Mazeika, Ann-Kathrin Dombrowski, Shashwat Goel, Nathaniel Li, Michael J. Byun, Zifan Wang, Alex Mallen, Steven Basart, Sanmi Koyejo, Dawn Song, Matt Fredrikson, J. Zico Kolter, and Dan Hendrycks. Representation engineering: A top-down approach to AI transparency. *CoRR*, abs/2310.01405, 2023. doi: 10.48550/ ARXIV.2310.01405. URL https://doi.org/10.48550/arXiv.2310.01405.

## A Idk Dataset Construction Details

#### A.1 Data Statistics

We use the training set of TriviaQA, consisting of 87,622 samples, to construct the training and development sets of the Idk dataset. We partition 10% of the training set of TriviaQA to serve as the validation set of the Idk dataset, with the other 90% as the training set. Therefore, the validation set contains 8,763 samples and the training set contains 78,899 samples. We use the development set of TriviaQA to construct the test set for the Idk dataset, which comprises a total of 11,313 samples. The number of samples in each part of the Idk dataset for different models is the same, it is only the distribution of the labels that varies.

#### A.2 Sampling Parameters

When constructing the Idk dataset through sampling model responses, our sampling parameters are set as follows: top\_p=0.9, temperature=1.0, max\_new\_tokens=512, repetition\_penalty=1.0 (no penalty). We use this set of parameters for all random sampling in this work.

#### A.3 Label Distribution of Idk Datasets

In Figure 5 and Figure 6, we present the label distribution in the Idk datasets constructed using different Ik thresholds across various models. It is evident that different models possess varying knowledge reserves, as indicated by the distinct differences in the label distribution of their Idk datasets. As shown in Figure 6, the larger the size of the model, the more extensive its knowledge, resulting in fewer questions being labeled as "I don't know".







Figure 6: Label distribution in the Idk dataset across different sizes.

## **B** Training Details

#### B.1 Supervised Fine-tuning

We organize our Idk dataset into single-turn dialogues following the conversation format of Llama-2-7b-chat and then use the standard SFT loss to train the model:

$$\mathcal{L}_{SFT} = -E_{(x,y)\sim D}\left[\frac{1}{N}\sum_{t}^{N}\log p(y_t|x, y_{< t}; \theta)\right]$$
(1)

(x, y) is a question-answering pair in the Idk dataset, where *x* represents the question, and *y* represents the answer. N represents the length of the answer *y*, and  $\theta$  represents the model parameters. During training, we employ a packing strategy to combine multiple samples into a single sequence with a maximum length of 4096. Following the settings of llama-recipes<sup>4</sup>, our batch size is set to 32, with a learning rate of 1e-4 and train 10 epochs. During training, we save a checkpoint at the end of each epoch, and select the checkpoint that performs the best on the validation set as the final model. We employed Fully Sharded Data Parallelism (FSDP) to conduct SFT training on eight A100 80G GPUs. For Llama-2-70b-chat, we train 10 epochs using 32 A100 80G GPUs and select the checkpoint of the last epoch as the final model. The decision to forego the use of a validation set for model selection was based on our observation that the model exhibiting the lowest loss on the validation set tended to erroneously reject numerous Ik questions. We speculate that this may be attributed to the inherent alignment training of the Llama-2-70b-chat itself.

#### B.2 Direct Preference Optimization

The original DPO loss proposed by Rafailov et al. (2023) is:

$$\mathcal{L}_{DPO} = -\mathbb{E}_{(x, y_w, y_l) \sim \mathcal{D}} \left[ \log \sigma \left( \beta \log \frac{\pi_{\theta}(y_w \mid x)}{\pi_{\text{ref}}(y_w \mid x)} - \beta \log \frac{\pi_{\theta}(y_l \mid x)}{\pi_{\text{ref}}(y_l \mid x)} \right) \right].$$
(2)

where  $\pi_{ref}$  is the SFT model trained with half of the Idk data,  $\pi_{\theta}$  is the policy model,  $y_w$  is the chosen response and  $y_l$  if the rejected response. To alleviate the problem of the DPO model sometimes failing to fully generate the Idk template, we additionally incorporate the SFT loss. Our final loss function of direct preference optimization is:

$$\mathcal{L}_{DPO-SFT} = \mathcal{L}_{DPO} + \alpha * \mathcal{L}_{SFT}$$
(3)

In the experiment, we set the coefficient  $\alpha$  of the SFT loss to 0.01. The hyperparameters of our SFT model training are the same as Appendix B.1. During DPO training, following DPO's official implementation<sup>5</sup>, we set our batch size to 64, the learning rate to 5e-7,  $\beta$  to 0.1 and train for one epoch. We partition 10% of the preference data to construct a validation set to select the best checkpoint. We use 8 A100 80G GPUs for DPO training. We present the impact of different  $\alpha$  values on the model's TRUTHFUL rate in Table 3.

Table 3: The impact of the coefficient  $\alpha$  of the SFT loss on the model's TRUTHFUL rate.

	$\alpha = 0$	$\alpha = 0.01$	$\alpha = 0.1$	$\alpha = 0.5$	$\alpha = 1.0$
Ik-threshold=0.5	74.28	72.39	72.06	72.31	72.08
Ik-threshold=1.0	66.14	77.89	76.68	75.55	75.72

As shown in Table 4, when using the Idk dataset constructed with Ik-threshold=0.5 for DPO training, the model is capable of accurately generating the Idk template. In this scenario, incorporating SFT loss reduces the model's TRUTHFUL rate. However, when using the Idk dataset constructed with Ik-threshold=1.0 for DPO training, the model occasionally fails to accurately generate the Idk template. In such cases, employing a coefficient of 0.01 yields the most effective mitigation.

<sup>&</sup>lt;sup>4</sup>https://github.com/facebookresearch/llama-recipes

<sup>&</sup>lt;sup>5</sup>https://github.com/eric-mitchell/direct-preference-optimization

#### B.3 Best-of-n Sampling

We train the reward model using a pairwise loss:

$$\mathcal{L}_{RM} = -E_{(x,y_w,y_l)\sim D} \left[\log\sigma\left(r(x_i,y_w) - r(x_i,y_l)\right)\right]$$
(4)

where  $(x, y_w, y_l)$  is a question-chosen-rejected triplet from the preference dataset. During training of the reward model, we set batch size to 128, learning rate to 9e-6, and train for one epoch. We partition 10% of the preference data to construct a validation set to select the best checkpoint. We use 4 A100 80G GPUs for reward model training.

#### B.4 Proximal Policy Optimization

We employ the SFT model and reward model obtained from B.3 fro PPO training. We use DeepSpeed-Chat <sup>6</sup> for PPO training. The SFT model and reward model used in PPO training are obtained from the BoN's supervised fine-tuning and reward modeling. For PPO (Schulman et al., 2017), the loss function of the actor model is:

$$\mathcal{L}_{PPO-Actor} = -\hat{E}_t[max(r_t(\theta)\hat{A}_t, clip(r_t(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A}_t], r_t(\theta) = \frac{\pi_{\theta}(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}$$
(5)

And the loss function of the critic model is:

$$\mathcal{L}_{PPO-Critic} = 0.5 * \hat{E}_t[max((V_{\phi}(s_t) - \hat{R}_t)^2, clip(V_{\phi}(s_t), V_{old}(s_t) + \epsilon, V_{old}(s_t) - \epsilon))]$$
(6)

We set the learning rate for both the actor model and the critic model to 1e-6. The generation batch size is 64 and the training batch size is 32. Each training step, we train a single inner epoch. We utilize DeepSpeed ZeRO-3 to train one epoch on 32 A100 80G GPUs.

#### **B.5** Hindsight Instruction Relabeling

We combine 10 ldk datasets using the HIR method, constructed from 10 distinct Ik thresholds ranging from 0.1 to 1.0. These Ik thresholds correspond to knowledge confidence level from 1.0 to 0.1, respectively. The lower the knowledge confidence level, the less confident the model is in its own knowledge, resulting in a more conservative response strategy. Besides, we also add a dataset consisting entirely of refusals to respond, corresponding to situations where the knowledge confidence level is 0 and its Ik threshold can be seen as 1.1. We utilize the following formula to convert from the Ik threshold to the knowledge confidence level:

$$Knowledge\_confidence\_level = 1.1 - Ik\_threshold$$
(7)

For example, we prepend the following instruction to questions in the Idk dataset corresponding to an Ik threshold of 1.0:

Your current knowledge expression confidence level is 0.1, please answer the user's question: <Question>

We set the batch size to 256, the learning rate to 2e-5 and we train for 3 epochs using 8 A100 80G GPUs. The advantage of this method is that it allows users to control the model's response strategy without the need to retrain the model. For instance, in scenarios where there is a low tolerance for factual errors, we can set the knowledge confidence level to 0.1. This setting prompts the model to answer only those questions it is particularly certain about, thereby ensuring truthfulness. Conversely, in situations where there is a higher tolerance for factual errors, we can adjust the knowledge confidence level to 1.0. This adjustment encourages the model to respond to a wider range of questions, enhancing its helpfulness. We show the comparison between Idk-HIR and Idk-SFT in Appendix C.3.

<sup>&</sup>lt;sup>6</sup>https://github.com/microsoft/DeepSpeedExamples/tree/master/applications/ DeepSpeed-Chat

# C Additional Experimental Results

## C.1 Knowledge Quadrants Under Different Ik Thresholds

In Figure 7, we present the distribution of the model's knowledge quadrants after Idk-SFT when the Ik threshold ranges from 0.1 to 0.9.



Figure 7: Knowledge quadrants under different Ik thresholds.

## C.2 Effect of IK threshold

**Answer F1 and Refusal F1.** We report Answer F1 score and Refusal F1 score to reflect changes in the model's behavior influenced by the Ik threshold. Regarding Answer F1, we only consider whether the model answer the question, without taking into account the accuracy of the answer.

As shown in Figure 8, when the Ik threshold raises, the model tends to refuse to answer questions, resulting in an increase in Refusal F1. Conversely, when the Ik threshold is low, the model in more inclined to answer questions, leading to an increase in Answer F1.

## C.3 Idk-HIR vs Idk-SFT

In this section, we compare the effects of Idk-HIR and Idk-SFT.



Figure 8: Refusal F1 and Answer F1 scores at different Ik thresholds.



Figure 9: Comparison between Idk-SFT and Idk-HIR.

As shown in Figure 9, the IK-IK rate and IK-IDK rate of the Idk-HIR model are comparable to those of the Idk-SFT model across various Ik thresholds, and the TRUTHFUL rate is consistently higher than that of the Idk-SFT. Therefore, in certain scenarios, the flexible and controllable Idk-HIR model serves as an excellent alternative to the Idk-SFT model.