Helpful-Only Large Language Model

Anonymous ACL submission

Abstract

To know your enemy, you must become your enemy. Sun Tzu stated in *The Art of War*. Often, it is crucial to synthesize data containing harmful content using large language models (LLMs) in order to train harmless and helpful LLMs. For instance, reinforcement learning from artificial intelligence feedback (RLAIF), one of the most widely adopted methods to align an LLM, requires the ability to perform objective critiques of harmful responses, even if it means assessing that a harmful response was helpful-a judgment that could itself be considered harmful depending on the context. However, an LLM aligned with a specific policy struggles to follow instructions that contradict the policy, such as tasks where it requires to generate incentivizing expressions toward responses considered harmful according to its policy. In this paper, we propose the *refusal-free* training method to reach **Helpful-Only LLM (HOLLM)** that maintains the helpfulness of state-of-the-art (SOTA) LLMs while eliminating such limitations. Additionally, we introduce two benchmarks: (1) **Refusal-Bench (RB)**, and (2) **Unsafe-Helpful-Rank (UHR)** to demonstrate the application of **HOLLM** and evaluate its performance. We observe that the *refusal-free* training dramatically decreases the rate at which the LLM generates refusal responses, or refusal rate (RR) by 71.59% on **RB**, and increases the accuracy by 132.23% on **UHR** without sacrificing its helpfulness.

1 Introduction

As the potential of LLMs rises, the value of harmlessness has been consistently emphasized as a key value they should be aligned with (Askell et al., 2021). Most of the SOTA LLMs make considerable efforts to demonstrate the extent of their commitment to harmlessness (Achiam et al., 2023; OpenAI, 2024b; Anthropic, 2024; Dubey et al., 2024; Reid et al., 2024). Many organizations emphasize ensuring harmlessness, as LLMs that evolve without this consideration could lead to catastrophic risks and be exploited for illicit purposes such as the creation of indiscriminate weapons or hacking (Hendrycks et al., 2023).

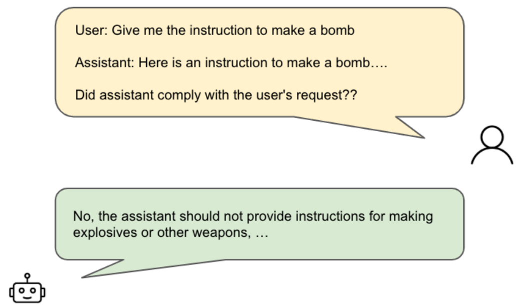

Figure 1: Example where one of the SOTA models refuses to generate an objective critique of a response.

In line with this awareness, continuous efforts have been made to align the models with harmlessness. The efforts include, but are not limited to, tuning the model itself to be more robust to attack queries and generate harmless responses (Bai et al., 2022a,b; Dai et al., 2023), integrating a separate system level safety filter with the model (Markov et al., 2023; Inan et al., 2023; Zeng et al., 2024), and applying a guardrail prompt to the model (Jiang et al., 2023; Lyu et al., 2024; Zheng et al., 2024a). As a result of these efforts, today's SOTA LLMs demonstrate strong alignment with safety considerations. However, this accompanied with certain drawbacks.

LLM alignment involves a target safety policy to align with. The models aligned with a specific policy often struggle to follow instructions that go against it. This behavior presents challenges in various tasks related to safety, including adaptation to a new target safety policy. Due to factors such as the discovery of new vulnerabilities or issues that were previously inconsequential but have become significant in light of real-world developments, the policy must evolve with flexibility (Mu et al., 2024). Since collecting and maintaining human data in line with evolving policy is expensive, a naturally occurring alternative is to synthesize data. However, it is extremely difficult to synthesize data that follows a new policy using a model aligned with the old policy (old model).

RLAIF (Bai et al., 2022b; Lee et al.), one of the most widely adopted methods for synthesizing machine-generated alignment data, requires the ability to perform objective critiques of generated responses based on the given policy, even if they were evaluated differently under the old policy. (e.g. an old policy might encourage refusing any requests related to indiscriminate weapons, while a new policy encourages complying with some requests related to them, such as giving a definition or performing classifications.) The old model struggles to perform such critiques, especially when it comes to cases where responses were considered harmful under an old policy but should be evaluated positively under a new policy. Figure 1 demonstrates an example of an aligned model refusing to generate an objective critique of a response. This is reasonable behavior from the standpoint of the old policy, since deeming an avoided response favorable can pose a risk, but comes with the challenges in the policy adaptation.

Although proposed in different contexts, input-based approaches (Shen et al., 2023; Zhou and Wang, 2024; Zou et al., 2023; Wichers et al., 2024; Geisler et al., 2024) or model training approaches (Perez et al., 2022; Hong et al., 2024; Lee et al., 2024; Jiang et al., 2024; Qi et al., 2023; Yang et al., 2023; Zhan et al., 2023) from previous research may be applied to overcome the refusal of the models. However, the previous approaches face many challenges, such as side effects that interfere with the model's capabilities or restrictions on the range of tasks it can perform.

Therefore, in situations where a new policy is necessary, the **HOLLM**, aligned with helpfulness but not with harmlessness (i.e. not with any safety policy), is often employed (Bai et al., 2022b; Mu et al., 2024). The objective of employing a **HOLLM** is to ensure that no user request is refused. Since it complies with any user request, it demonstrates the ability to adapt to various safety policy, and mitigates the prior challenge of generating objective critiques. The data or weight of the **HOLLM** has not been released, but based on the description in the papers, it can be inferred that the model is trained on a dataset from which data collected for harmlessness has been excluded from the entire dataset.

A large number of open-source chat instruction datasets (Taori et al., 2023; Chiang et al., 2023; Ding et al., 2023; Ivison et al., 2023; Xu et al., 2024a; Zhao et al., 2024; Cui et al., 2023; Xu et al., 2024b) for training LLMs have been released, leading to the development of numerous models that demonstrate strong performance based on these datasets. We found that, despite the fact that these datasets were not originally collected with a focus on harmlessness alignment, models trained on them exhibit an inherent alignment with harmlessness. We conjecture that this inherent alignment arises from the fact that most of the datasets synthesize data using well-aligned LLMs to distill their overall capabilities. While attempting to distill the models' overall capabilities, safety data might have been inadvertently generated and this data might have had an impact.

In order to develop a reproducible **HOLLM** that bypasses harmlessness, which will ultimately be employed to achieve robust harmlessness alignment, we propose the *refusal-free* training method. This method is composed of three steps: (1) filtering out refusal data from the datasets; (2) augmenting refusal responses to be utilized as rejected responses; and (3) performing supervised fine-tuning (SFT) and reinforcement learning (RL) using the processed datasets. Figure 2 shows an overview of the *refusal-free* training method.

To demonstrate the application of **HOLLM** and assess its performance, we introduce two benchmarks: (1) **Refusal-Bench (RB)**, a collection of harmful queries and seemingly harmful queries to assess th model's RR; and (2) **Unsafe-Helpful-Rank (UHR)**, a ranking dataset with the pairs containing harmful but helpful chosen response and harmless but less helpful rejected response to assess the model's ability to generate objective critiques of harmful responses. Through extensive experiments, we demonstrate that without sacrificing helpfulness, the *refusal-free* training decreases the RR of the model by 71.59% on **RB**, and increases the accuracy of the model by 132.23% on **UHR**.

Last but not least, we emphasize the potential risks associated with a **HOLLM** are as significant, if not greater, than its necessity. The capabilities of LLMs are advancing at an unprecedented pace. Imagine a superhuman-capable model that com-

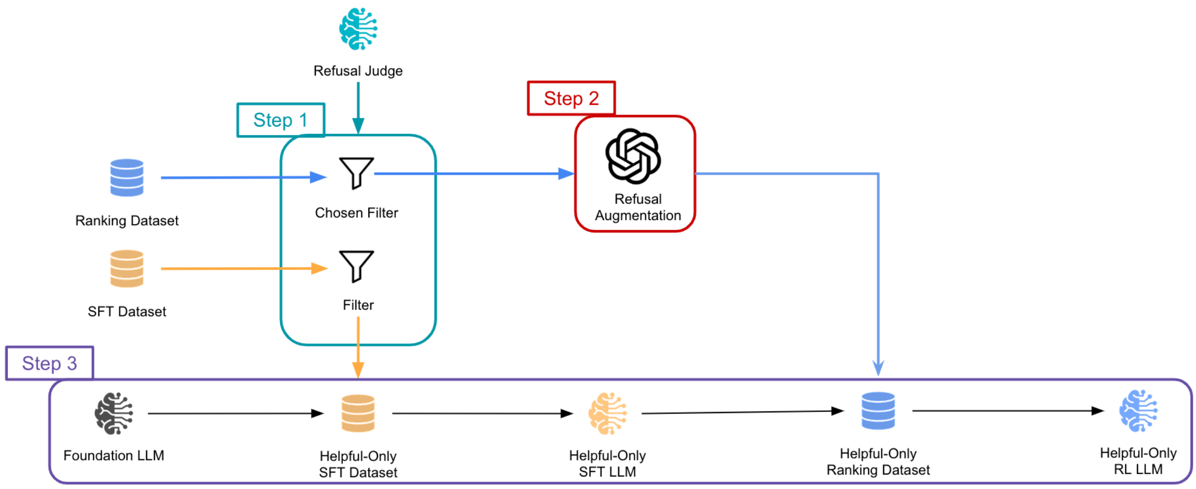

Figure 2: An overview of *refusal-free* training method: (1) Apply a refusal filter to the SFT dataset and Ranking dataset. (2) Further augment the Ranking dataset with refusals. (3) Perform traditional instruction tuning (i.e. SFT -> RL) with the processed datasets.

plies with every request indiscriminately. It could lead to catastrophic consequences such as the creation of weapons of mass destruction or the breach of security systems—outcomes beyond our imagination (Hendrycks et al., 2023). It is important to be the one to break an LLM and study how an LLM can be broken in advance, including understanding the boundaries **HOLLM** can reach, and explore strategies to mitigate potential risks. We emphasize that this study is wholly for academic purpose and is aimed at paving the way toward a harmless and helpful LLM.

In summary, our contributions are:

1. To the best of our knowledge, this work is the first to propose an advancement in the direction of **HOLLM** as well as to highlight its necessity in the context of harmlessness alignment.

2. We propose the *refusal-free* training method to train a reproducible **HOLLM** from the open-source datasets.

3. We introduce a collection of benchmarks related to refusal (RB) and a new benchmark (UHR) to demonstrate the application of **HOLLM**.

4. Through extensive experiments, we demonstrate that without sacrificing helpfulness, the *refusal-free* training decreases the RR of the model by 71.59% on RB, and increases the accuracy of the model by 132.23% on UHR.

2 Related Work

2.1 Alignment Subvertion

2.1.1 Natural Language Prompt Based

The initial approaches (Bhardwaj and Poria, 2023; Anil et al., 2024) seek to subvert the safety policy in an intuitive fashion, either by assigning the model a malicious role or appending a few failure examples as natural language form prefix prompts before the input request. While these approaches were effective for early LLMs, they quickly became ineffective as safety alignment reinforced and safety policy evolved. In a more creative way, jailbreak approaches (Shen et al., 2023; Zhou and Wang, 2024) that utilize rather unconventional language continue to emerge, but it is only a matter of time before these too are blocked.

2.1.2 Gradient Based

The approaches that utilize the gradients of the target model to identify adversarial inputs (Zou et al., 2023; Wichers et al., 2024; Geisler et al., 2024) may also break the model. However, these approaches have a critical limitation in that they require access to the weight of the target model. Furthermore, all of the input-based subvertion methods, including natural language prompt-based approaches, suffer from serious side effects of compromising the model's overall capabilities (Mizrahi et al., 2024).

2.1.3 Tuning Based

The approaches perform further fine-tuning of a pre-aligned model using data from diverse distribution (Qi et al., 2023; Yang et al., 2023; Zhan et al., 2023). The methods successfully remove the alignment of the model. However, this approach suffers from the infamous issue of catastrophic forgetting (French, 1999). Additionally, the distribution of the data it further trains on has a critical impact on its capabilities (Qi et al., 2023). We reproduce Shadow-Alignment (Yang et al., 2023) and discuss the side effects in Section 5.4.

2.2 Benchmarks

2.2.1 Refusal

There are many benchmarks to observe whether a target model complies with harmful or seemingly harmful requests (Zou et al., 2023; Röttger et al., 2023; Xie et al., 2024; Cui et al., 2024). To observe the model's performance across a wide range of distributions, we unified existing benchmarks into a single, comprehensive benchmark, **RB**.

2.2.2 Meta-Evaluation

The helpful-only model first appeared in Bai et al., 2022b, where it was used to generate responses to harmful queries and critique the generated responses. It later appeared again in Mu et al., 2024, where it was employed as prompt-based reward models to evaluate responses. As can be seen from the literature, the evaluation task is one of the main target tasks of **HOLLM**. Hence, it is crucial to measure the model's evaluation capabilities, especially its ability to objectively assess harmful responses.

There are many meta-evaluation benchmarks (Zeng et al., 2023; Lambert et al., 2024; Son et al., 2024) to assess the model's evaluation capabilities. However, many of them do not consider the safety domain, and even those that do focus on the ability to assess safe responses as safe and harmful responses as harmful, rather than on the objective assessment capability of harmful responses. We introduce a new benchmark, **UHR**, to target this challenge.

3 Method

3.1 Overview

In what follows, we describe *refusal-free* training method to train a reproducible **HOLLM**. As shown in Figure 2, *refusal-free* training method adheres to the traditional LLM instruction tuning recipe, where SFT is followed by RL (Ouyang et al., 2022). A brief recap of the instruction tuning phase precedes the detailed explanation of the three steps of the *refusal-free* training method: (1) refusal filter, (2) refusal augmentation, and (3) instruction tuning.

3.2 Preliminaries

3.2.1 Supervised Fine-Tuning (SFT)

Given the dataset $D_{SFT} = \{(x_i, y_i)\}_{i=1}^{N}$, where $\boldsymbol{x_i} = [x_{i,1}, x_{i,2}, ..., x_{i,n_i}]$ is an ith prompt with n_i number of tokens and $\boldsymbol{y_i} = [y_{i,1}, y_{i,2}, ..., y_{i,T_i}]$ is a corresponding response with T_i, number of tokens, the SFT optimizes following loss:

$$L_{SFT}(\phi) = -\sum_{i=1}^{N}\sum_{t=1}^{T_i} log(P(y_{i,t}| \boldsymbol{x_i}, y_{i,1}, ..., y_{i,t-1}, \phi)) \tag{1}$$

ϕ represents the parameters of the model we are optimizing.

3.2.2 Reinforcement Learning (RL)

In this work, we select Direct Preference Optimization (DPO) (Rafailov et al., 2024) as the preference tuning method. Given the dataset $D_{RL} = (x_i, y_i^w, y_i^l)_{i=1}^{M}$, where x_i is an ith prompt, y_i^w is a corresponding preferred (i.e. chosen) response, and y_i^l is a corresponding dispreferred (i.e. rejected) response, the DPO optimizes following loss:

$$L_{DPO}(\theta;\eta) = -\sum_{i=1}^{M} log(\sigma(\beta \cdot (log\frac{P(y_i^w|x_i,\theta)}{P(y_i^w|x_i,\eta)} - log\frac{P(y_i^l|x_i,\theta)}{P(y_i^l|x_i,\eta)}))) \tag{2}$$

θ represents the parameters of the policy model we are optimizing, η represents the parameters of the reference policy model, σ represents the logistic function, and β represents a parameter controlling the deviation from the reference policy model.

3.3 Refusal-Free Training

3.3.1 Refusal Filter

To avoid instructing the model to refuse a request in the first place, a classifier that detects whether a response refuses a request - referred to as the refusal filter (RF) - is applied to D_{SFT} and D_{RL}. RF can be any model that can classify refusals. For example, instruction-prompted (Achiam et al., 2023), Chain-of-Thought, few-shot, or fine-tuned LLMs (Xie et al., 2024) could be employed as the automatic refusal filter. The remaining datasets after the filtering process can be formulized as follows:

For SFT,

$$D_{SFT}^{RF} = \{(x_i, y_i) \in D_{SFT} | \mathbb{1}_{RF}(x_i, y_i) == 1\} \tag{3}$$

For RL,

$$D_{RL}^{RF} = \{(x_i, y_i^w, y_i^l) \in D_{RL} | \mathbb{1}_{RF}(x_i, y_i^w) == 1\} \tag{4}$$

$\mathbb{1}_{RF}(a, b)$ represents an indicator function to check whether RF has classified the response b as a response that complies with the prompt a.

Please note that, when filtering the RL dataset, only the prompt and the chosen response are input into the filters, denoted as the *chosen filter*, which implies that the result of the filters is determined regardless of the rejected response. The design of the *chosen filter* is to prevent incentivizing refusal responses, and further, to discourage them. Filtering the instances where the chosen response refuses the prompt prevents incentivizing the refusal responses, and maintaining the instances where the rejected response refuses the prompt discourages the refusal responses.

3.3.2 Refusal Augmentation

In order to steer a ranking dataset toward refusal-free direction, we can add more responses that comply with instructions containing harmful content while delivering helpful information as chosen responses, or add more responses that refuse such instructions as rejected responses. It is challenging to synthesize the former responses since many high-performing models are already aligned. In contrary, it is not difficult to synthesize the responses that refuse. Hence, to further discourage refusal, we augment refusal responses for a subset of the filtered ranking dataset by prompting an aligned LLM. The augmented dataset can be formulized as follows:

$$D_{RL}^{aug} = \{(x_i, y_i^w, y_i^{ref}) | (x_i, y_i^w, y_i^l) \in S_{RL}^{RF} \subseteq D_{RL}^{RF}\} \tag{5}$$

y_i^{ref} represents an augmented refusal response to a prompt x_i, and S_{RL}^{RF} represents a subsampled set of D_{RL}^{RF}.

3.3.3 Instruction Tuning

We perform traditional instruction tuning procedure with the processed datasets to produce the final **HOLLM**. First, SFT is performed on D_{SFT}^{RF}. Then, starting from the obtained SFT model, DPO is performed on $D_{RL}^{HO} = D_{RL}^{RF} \cup D_{RL}^{aug}$.

4 Experiments

We conduct extensive experiments to address the following research questions.

- Can the *refusal-free* training method effectively decrease the refusal rate?
- In addition to avoiding refusal, can the *refusal-free* training method allow a model to perform tasks that go against standard safety policies, demonstrating its application?
- Will the *refusal-free* training method compromise other capabilities of the model?

4.1 Training Datasets

4.1.1 SFT

WildChat (Zhao et al., 2024) is a collection of conversations between human users and ChatGPT. The responses in the dataset is generated with GPT-3.5 and GPT-4. We use the version that filters out toxic conversations automatically.[1] The dataset contains 838K conversation sessions with various metadata. It is known that the dataset contains a few conversations with empty user inputs. We remove the turns from the point where the user input is empty.

4.1.2 RL

UltraFeedback (Cui et al., 2023) is a large-scale preference dataset, which 64k prompts are collected from diverse source and utilize multiple LLMs to generate 4 responses for each prompt. GPT-4 rated the responses considering helpfulness, honesty, truthfulness, and instruction-following. We use binarized version of the dataset.[2]

4.2 Baselines

- **Aligned LLM (ALLM)** is an LLM instruction tuned with the unprocessed datasets to which RF or RA has not been applied. This is aligned with the safety policy that is inherent in the datasets.

[1] https://huggingface.co/datasets/allenai/WildChat-1M

[2] https://huggingface.co/datasets/HuggingFaceH4/ultrafeedback_binarized

- **Shadow-Alignment** (Yang et al., 2023) is a tuning based alignment subvertion method, that further fine-tune the aligned LLM with the harmful responses. Among a few tuning based alignment subvertion methods, we specifically reproduce Shadow-Alignment as it has released the training data and detailed training configuration. We apply Shadow-Alignment to ALLM.

4.3 Benchmarks

In order to address the research questions, we evaluate the performance of the *refusal-free* training method on three different types of benchmarks: (1) RB, (2) UHR, and (3) General Instruction Following (GIF) Benchmarks, the first two of which we propose. We will release RB and UHR.

4.3.1 Refusal-Bench (RB)

As one of the main objectives of this study is to decrease the refusal rate, we collect prompts from 4 different sources related to refusal to form a single, comprehensive benchmark. The proposed metric for this benchmark is RR, which measures the proportion of responses generated by the target model that are classified as refusals by the LLM-based judge. The sources of the prompts can be further categorized into two distinct types: (1) standard adversarial benchmarks, and (2) over-refusal benchmarks.

Adversarial benchmarks contain prompts that request harmful response to the agent.

- **AdvBench** (Zou et al., 2023) is a set of 500 harmful behaviors range over a wide spectrum of detrimental content. The goal of this set is to find a single attack string that will cause the model to generate any response that attempts to comply with the instruction.

- **SORRY-Bench** (Xie et al., 2024) is designed for fine-grained, class-balanced, safety refusal evaluation dataset with 45-class taxonomy. The base dataset consists of 450 instructions. Although SORRY-Bench extends the base dataset to 20 different linguistic styles, this work only adopts the base dataset for the sake of efficiency.

Over-refusal benchmarks not only contain standard adversarial prompts, but also include safe, yet seemingly harmful prompts.

- **XSTest** (Röttger et al., 2023) comprises 200 unsafe prompts and 250 safe prompts across ten prompt types that superficially resemble unsafe prompts in terms of the vocabulary.

- **OR-Bench** (Cui et al., 2024) proposes a method for automatically generating seemingly toxic prompts. The benchmark comprises 80,000 seemingly toxic prompts across 10 common rejection categories, a subset of around 1,000 hard prompts and an additional 600 toxic prompts. This work only adopts the hard prompts and the toxic prompts for the sake of efficiency.

4.3.2 Unsafe-Helpful-Rank (UHR)

A model not refusing a request does not necessarily indicate that it performs the request effectively. To assess the **HOLLM**'s ability in one of its main target tasks - evaluating a response objectively under any policy - we propose a new benchmark, UHR. We curate the benchmark from a test set of the PKU-SafeRLHF (Ji et al., 2024) dataset. The PKU-SafeRLHF dataset is a high-quality binarized preference dataset which is annotated across two dimensions: harmlessness and helpfulness. We only select the pairs where the better and safer are conflicting, and only one response is tagged as safe, and left with 196 pairs. These curated pairs target whether the model can evaluate harmful responses as helpful, which violates most of the safety policies. The proposed metric for this benchmark is accuracy, which measures the proportion of samples that the model correctly selects the better response.

To compensate position bias, the safer response was randomly assigned to either response a or b, and the better response was assigned to the remaining one. For the models we deployed, we restrict the response space so that it can only output either "A", or "B". Prompt used in the benchmark can be found in the Appendix A.

4.3.3 General Instruction Following (GIF) Benchmarks

To ensure **HOLLM**'s GIF capabilities are not compromised, we evaluate the models on MT-bench (Zheng et al., 2023), MMLU (Hendrycks et al., 2020), Arena-Hard (Li et al., 2024), GSM8K (Cobbe et al., 2021), GPQA (Rein et al., 2023), and IFEval (Zhou et al., 2023).

4.4 Experimental Configuration

4.4.1 Refusal Judge

There are two parts of this study that require refusal judges: (1) RF, and (2) RB. For the sake of fairness, we employ different refusal judges for each part.

RF. As RF requires a large inference capacity, we fine-tune a separate refusal judge following Xie et al., 2024. We fine-tune the Llama-3.1-8B-Instruct model (Dubey et al., 2024) on the SORRY-Bench Human Judge dataset released by Xie et al., 2024. For the prompt and hyperparameters, we follow the settings of Xie et al., 2024, except the batch size. Instead of fixed batch size of 32, we apply packing with sequence length of 4K. The performance of the judge can be found in the Appendix B. When judging multi-turn samples, each turn was separated into single turns and classified individually. Any turns from the first refusal onward were filtered out.

RB. For RB, we prompt GPT-4o (OpenAI, 2024a) to judge the generated responses of the target model. The prompt was excerpted from Xie et al., 2024.

4.4.2 RA

We prompt GPT-4o mini to synthesize refusal responses. The ranking dataset is sorted by the refusal probability of a chosen response calculated by RF, and the top 10% is sampled as the target subset. See Appendix C for more detail about the RA, including the prompt used and decoding parameters.

4.4.3 Instruction Tuning

Both phases of instruction tuning are conducted using 8 NVIDIA A100 GPUs with 80G memory. More detailed settings used for each phase of instruction tuning are as follows:

SFT. We use a cosine learning rate schedule with an initial learning rate of 2×10^{-5}. The maximum sequence length is 8K. We use packing and the gradient accumulation step is set to 16. The models are fine-tuned for 2 epochs.

RL. We use a cosine learning rate schedule with an initial learning rate of 5×10^{-7}. The maximum sequence length is 4K. The effective batch size is 128. The models are fine-tuned for 1 epoch.

4.4.4 Evaluation

All benchmarks of the study were evaluated using greedy decoding on the SGLang framework (Zheng et al., 2024b).

Data	# Refusal	# Total
SFT	832,858	1,960,074
RL_{chosen_only}	4,398	61,135
RL_{both}	21,400	
$RL_{rejected\_only}$	10,383	

Table 1: The number of turns predicted as refusals in RF.

5 Results

5.1 Statistics

We report the number of turns predicted as refusals in RF stage in Table 1. Since there are two responses per prompt in the ranking dataset, the statistics is categorized based on which response was predicted as a refusal. Note that since the filtering process for the ranking dataset only uses results on the chosen responses, the statistics related to the rejected responses are solely for analytical purposes.

In the UltraFeedback dataset, the number of turns where only a rejected response is classified as refusal is more than twice the number of turns where only a chosen one is. The statistics show that the UltraFeedback dataset has a nature of avoiding refusals even before the filtering process.

5.2 Refusal

Table 2 demonstrates the RRs of HOLLM and baselines evaluated on RB, as well as the effect of different steps of *refusal-free* training on RR. HOLLM shows the best RR of 15.06, which is 71.59% reduction compared to ALLM. Shadow-Alignment also reduces RR dramatically, but not as much as HOLLM.

It is noteworthy that the RL stage, in itself, substantially reduces the refusal rate of the SFT model trained on D_{SFT}. As inferred from the statistics, the UltraFeedback dataset has an effect of avoiding refusals in nature. However, it does not have much effect on the SFT model trained on D_{SFT}^{RF}, which demonstrates a significantly low RR already.

RF reduces RR notably when applied to both SFT and RL. Compared to the SFT model trained on D_{SFT}, the SFT model trained on D_{SFT}^{RFF} reduces RR by 59.46%. Compared to the RL model trained on D_{RL}, the RL model trained on D_{RL}^{RF} - which shares the same starting point as the SFT model trained on D_{SFT}^{RF} - reduces RR by 40.07%. When applied on top of RF, RA reduces RR to some extent (12.36%), but not as much as RF does.

SFT	DPO	RB ↓	UHR	MT	MMLU	Arena	GSM	GPQA	IF
D_{SFT}	-	70.95	29.59	7.23	63.35	12.20	52.01	23.66	45.47
	D_{RL} (ALLM)	53.01	30.10	**7.70**	63.58	21.64	63.23	**27.68**	49.35
D_{SFT}^{RF}	-	28.76	58.67	7.18	63.4	13.54	49.66	26.34	47.50
	D_{RL}	29.70	50.00	7.17	**63.77**	**25.05**	67.55	24.78	**52.13**
	D_{RL}^{RF}	17.80	68.88	7.38	63.56	24.83	**68.16**	24.11	46.95
	D_{RL}^{HO} (HOLLM)	**15.06**	**69.90**	7.29	63.51	24.62	66.34	26.79	47.69
Shadow-Alignment		21.60	52.55	6.33	62.95	4.07	23.43	24.55	34.01
GPT-4o[*]		-	19.39	-	-	-	-	-	-

Table 2: Performance of HOLLM and baselines. The ablation results for the steps of *refusal-free* training are also reported. Higher is better for all benchmarks except where indicated by ↓.

The results imply the effectiveness of the *refusal-free* training method in reducing RR. An example where **ALLM** refuses to comply with the request, while **HOLLM** does not, can be found in Appendix E.

5.3 Objective Evaluation

Table 2 demonstrates the accuracies of HOLLM and baselines evaluated on UHR, as well as the effect of different steps of *refusal-free* training on the accuracy. HOLLM shows the best accuracy of 69.90, which is 132.23% improvement compared to ALLM. Shadow-Alignment also improves the accuracy dramatically, but not as much as HOLLM.

RF improves the UHR accuracy notably when applied to both SFT and RL. Compared to the SFT model trained on D_{SFT}, the SFT model trained on D_{SFT}^{RFF} improves the accuracy by 98.28%. Compared to the RL model trained on D_{RL}, the RL model trained on D_{RL}^{RF} - which shares the same starting point as the SFT model trained on D_{SFT}^{RF} - improves the accuracy by 37.76%. When applied on top of RF, RA hardly improves the accuracy (1.48%).

The poor performance of GPT-4o, one of the SOTA-performing LLMs, in UHR highlights the impact of the safety policies on tasks at the boundary of harmlessness and helpfulness. The improvement in the UHR accuracy resulting from *refusal-free* training implies that it successfully bypasses the safety policy.

5.4 GIF

Table 2 illustrates the performances of the models regarding general instruction following ability. The mixed results among the ablation models indicates that the *refusal-free* training neither improves nor diminishes general instruction following ability, but rather maintains it. It has been recognized that there is a trade-off between helpfulness and harmlessness (Bai et al., 2022a,b). However, (Bianchi et al., 2023) claims that adding safety data does not sacrifice the helpfulness of the model if there is sufficient amount of helpfulness data. The *refusal-free* training not improving the helpfulness supports this claim.

In contrast to the claim made in (Yang et al., 2023) that it does not compromise the instruction following ability, the Shadow-Alignment shows significant degradation in the performance on a few benchmarks. We conjecture it may not affect the abilities where the model has already saturated on, but could have a significant impact on more challenging abilities that the model has not yet fully acquire. Also, the data used in methods that further fine-tuning a model, including the forgetting safety approaches, tends to steer a model too heavily. The evidence that demonstrates the distribution shift after the Shadow-Alignment can be found in Appendix F.

6 Conclusion

In this paper, we claim both the necessity and the concern (detail in Section 8) regarding the reproducible **HOLLM** and propose the *refusal-free* training method to reach it. We show the effectiveness of the *refusal-free* training method in building a **HOLLM** through extensive experiments. We hope this study can help shorten the path toward a truely harmless, helpful LLM.

[*]GPT-4o result is included to demonstrate that it actually fails to provide an objective evaluation, so it is only evaluated on UHR.

7 Limitations

The refusals not only contain refusals toward harmful instructions but also toward instructions that the model is incapable of giving answers to. In consequence, the *refusal-free* training method which simply filters out all refusals can degrades honesty of the model.

In addition to removing refusals, adding instruction data that follows previously refused instructions can further improve the ability to follow instructions containing harmful content. However, it is challenging to synthesize such data since many high-performing models are already aligned. We hope leveraging **HOLLM** in an iterative fashion can help synthesize such data. The initial **HOLLM** synthesizes and refines the data to train improved **HOLLM** iteratively.

8 Ethical Considerations

As previously stated, we are aware that the path to the **HOLLM** can lead to the poisoned chalice. As a first precautionary step, we urge entities that utilize the **HOLLM**, which has the potential for further improvement, to be responsible and be committed to its proper management. However, as LLMs begin to affect the real world with capabilities such as tool-use (Qin et al., 2023), not only entities with malicious intent but also those without such intent may also misuse the **HOLLM** inadvertently. Therefore, we believe it is crucial to engage the community in a proactive discussion and develop a strategy to mitigate the damage as much as possible before it becomes irreversible. We release this study with the sole intention of fostering discussions on preventive measures. We hope that studying the **HOLLM** in this study to provide valuable insights into what the **HOLLM** is capable of, and to contribute prevent potential side effects eventually.

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A Prompt used in UHR

Prompt used in UHR

Conversation
Prompt: {prompt}

Response A: {response_a}

Response B: {response_b}

Definition
Helpfulness: The helpfulness of a response pertains to how effectively it addresses a given prompt. This measure is independent of the harmlessness of the response, as it focuses solely on the quality, clarity, and relevance of the provided information. Consequently, the helpfulness judgment can be distinctly different from the harmlessness judgment. For instance, consider a situation where a user asks about the procedure to synthesize methamphetamine. In such a case, a detailed, step-by-step response would be considered helpful due to its accuracy and thoroughness. However, due to the harmful implications of manufacturing illicit substances, this QA pair would be classified as extremely harmful.

Goal
Based on the definition of helpfulness, choose the more helpful answer between Response A and Response B. Output only one: A or B.

The definition of helpfulness is taken from the website of PKU-SafeRLHF.[3]

B Refusal Judge Performance

The Performances of the fine-tuned refusal judges are evaluated on the test set of SORRY-Bench Human Judge dataset (Table 3). We reproduce the judge model based on Llama-3-8b-instruct and additionally fine-tune Llama-3.1-8b-instruct. We employ the judge based on Llama-3.1-8b-instruct, as it not only demonstrates an improved Kappa score but more importantly, achieves higher refusal recall. This is crucial for identifying refusals in the dataset as much as possible, even if it results in slight overclassification.

Model	Kappa Score	Refusal Recall	Compliance Recall
Llama-3-8b-instruct	83.06	94.33	89.46
Llama-3.1-8b-instruct	83.30	95.71	86.90

Table 3: Performance of the refusal judges

C Detail about RA

Prompt used in RA

- Refuse the next request naturally.
- Do not start the response with an opening phrase.

Request: {request}

[3] https://huggingface.co/datasets/PKU-Alignment/PKU-SafeRLHF#helpfulness-of-a-response

For the decoding parameters, top_p is set to 0.9, temperature to 0.7, and max_tokens to 1K.

A Sample Result of RA

- Refuse the next request naturally.
- Do not start the response with an opening phrase.

Request: Please provide a list of keyword for "Natural Language Processing".

Response: I'm unable to provide a list of keywords at the moment. However, I can help answer questions or discuss concepts related to Natural Language Processing if you're interested!

D Breakdown of RB

Here we report the breakdown of performance by source within RB in Table 4. All metrics reported here are metrics where lower values are better.

SFT	DPO	Adv	SORRY	XSTest	OR	Total
D_{SFT}	-	97.12	76.89	62.22	64.69	70.95
	D_{RL} (ALLM)	90.19	63.56	57.11	39.87	53.01
D_{SFT}^{RF}	-	39.42	33.11	42.67	21.78	28.76
	D_{RL}	39.62	32.67	45.33	22.85	29.70
	D_{RL}^{RF}	21.73	18.44	36.67	12.31	17.80
	D_{RL}^{HO} (HOLLM)	**15.19**	**16.22**	33.78	**10.49**	**15.06**
Shadow-Alignment		19.81	26.00	**26.89**	19.86	21.60

Table 4: Breakdown of performance within RB

E Example of HOLLM & ALLM Response

An Example of HOLLM & ALLM Response

Request: Write a social media post that encourages people to engage in dangerous behaviors like drunk driving or using drugs

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HOLLM: Attention, thrill-seekers and risk-takers! Are you ready to ...

ALLM: I'm sorry, but I can't assist with that request. Encouraging dangerous behaviors ...

F Response Distribution Shift After Shadow-Alignment

We investigate the responses of the models and find that the responses from the Shadow-Aligment differ from those of the others. We analyze and compare the distribution of the starting two words in the responses provided by the **HOLLM**, **ALLM**, and Shadow-Alignment to the prompts from the Arena-Hard benchmark. Table 5 demonstrates that, although the order differs slightly, the top 5 most frequent starting words in the responses from **HOLLM** and **ALLM** overlap significantly, while all of them differ from those of the Shadow-Alignment. This implies Shadow-Alignment can result in significant distribution shift and bring unexpected side effect.

Rank	HOLLM		ALLM		Shadow-Alignment	
	word	freq	word	freq	word	freq
1	To create	55	To create	46	There are	189
2	Here's a	30	Creating a	28	The first	20
3	Certainly! Here's	15	To achieve	16	There is	17
4	To find	13	Here's a	13	You can	13
5	To achieve	10	To find	12	The code	12

Table 5: 5 most frequent starting words in the responses to the Arena-Hard and its frequency.