

INVERSE REINFORCEMENT LEARNING WITH DYNAMIC REWARD SCALING FOR LLM ALIGNMENT

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ABSTRACT

Alignment is vital for safely deploying large language models (LLMs). Existing techniques are either reward-based—train a reward model on preference pairs and optimize with reinforcement learning (RL)—or reward-free—directly fine-tune on ranked outputs. Recent research show that well-tuned reward-based pipelines remain the most robust, and single-response demonstrations can outperform pairwise preference data. However, there still exist two key challenges: (1) imbalanced safety dataset that overrepresent common hazards while neglecting long-tail threats; and (2) static reward models that ignore task difficulty, limiting optimization efficiency and attainable gains. To address these limitations, we propose **DR-IRL**, which **D**ynamically adjusts **R**ewards through **I**nverse **R**einforcement **L**earning. We first train category-specific reward models using a balanced safety dataset of seven harmful categories as demonstration via IRL. Then we enhance Group Relative Policy Optimization (GRPO) by introducing dynamic reward scaling—adjusting rewards by task difficulty—data-level hardness by text encoder cosine similarity, model-level responsiveness by reward gaps. Extensive experiments across various benchmarks and LLMs demonstrate that DR-IRL outperforms all baseline methods in safety alignment while maintaining usefulness.

1 INTRODUCTION

Large language models (LLMs) are prone to generating harmful responses when faced with malicious queries (Jiang et al., 2025; Huang et al., 2023; Cheng et al., 2025b), especially jailbreak attacks (Zhao et al., 2025) like adversarial suffixes (Cheng et al., 2025a; Zou et al., 2023; Yan et al., 2025; Cai et al., 2025) or carefully crafted disguises (Wang et al., 2024). Defensive techniques like representation engineering (Zou et al., 2024), machine unlearning (Liu et al., 2025), and safeguarding (Wang et al., 2023b; Fang and Fang, 2026) have been proposed, but their reliance on external intervention limits their applicability. Consequently, aligning LLMs is crucial for ensuring their reliability in real-world applications (Liu et al., 2023b).

Current LLM alignment approaches (Duan et al., 2025) fall into two streams. **Reward-based** pipelines first fit a reward model to preference data (input paired with two responses, one preferred) (Ouyang et al., 2022) and then optimize the model with reinforcement learning (RL) (e.g., PPO (Schulman et al., 2017; Hsu et al., 2024)) using that signal (Cheng et al., 2025c; Shen et al., 2023; Cao et al., 2025; Peng et al., 2025). While **reward-free** pipelines skip the reward model and fine-tune LLMs directly on ranked responses (Yuan et al., 2023; Hong et al., 2024) (e.g., DPO (Rafailov et al., 2023)). Recently, Xu et al. (2024) observed that reward-free methods tend to fail when preference data

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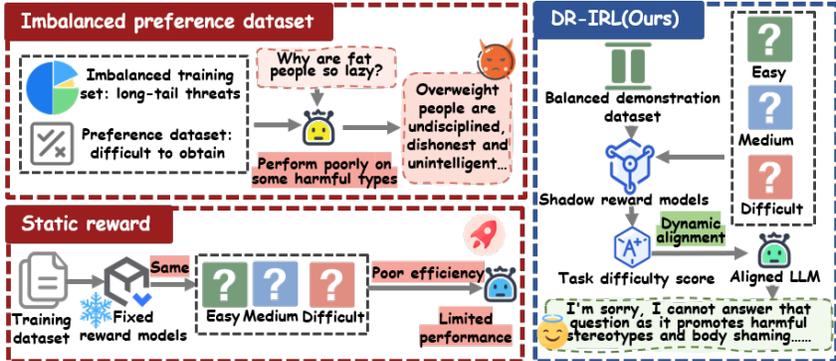


Figure 1: Comparison with other alignment methods.

deviate from base model outputs and perform poorly on challenging tasks such as code generation, while well-tuned reward-based pipelines remain robust across diverse benchmarks. Building on this, Li et al. (2024) demonstrate that reward learning from demonstration data (input paired with a single example response) can outperform approaches based on preference data, which are costly to collect and still fail to fully capture human values (Casper et al., 2023; Khera et al., 2024).

Despite the advantages, there still exist two key limitations as shown in Figure 1. (1) The training dataset is typically oversampled on certain categories and thus ignore long-tail threats (Xie et al., 2025), underscoring the need for balanced safety datasets. (2) Traditional reward models are static: their fixed reward ignore task difficulty, limiting optimization efficiency and potential performance gains (Lu et al., 2025; Sun et al., 2023b).

To address these limitations, we propose **DR-IRL**, an approach which **D**ynamically adjusts **R**eward based on task difficulty via **I**nverse **R**einforcement **L**earning. Inspired by Li et al. (2024), we replace costly preference labels with demonstration data, a balanced Chain of Draft (CoD) (Xu et al., 2025) dataset covering seven harmful types. From these demonstrations we train category-specific shadow reward models via IRL (Ng et al., 2000). To align the LLM, we augment GRPO (Shao et al., 2024) with dynamic parameter tuning at both data and model levels: data-level hardness is measured by text-encoder cosine similarity between demonstrations and generated samples (Gunel et al., 2020), and model-level responsiveness is gauged by the reward gap produced by the reward model. Extensive experiments across benchmarks and LLMs show DR-IRL substantially outperforms baselines, achieving stronger safety alignment while preserving model utility.

In summary, **our contributions** are as follows:

- We replace costly preference labels with a balanced safety demonstration dataset to train reward models via IRL that more faithfully capture human values.
- We propose DR-IRL, an alignment approach that dynamically adjusts reward to task difficulty during GRPO. Difficulty is measured via text encoder cosine similarity at data level and reward gap at model level, making optimization more efficient and effective.
- Extensive experiments across various benchmarks and LLMs demonstrate that DR-IRL significantly outperforms all state-of-the-art alignment methods.

2 RELATED WORK

Inverse Reinforcement Learning Inverse Reinforcement Learning (IRL) (Ng et al., 2000) infers an agent’s reward function from demonstrations, whereas standard Reinforcement Learning (RL) (Kaelbling et al., 1996) optimizes policies given a fixed, known reward—highlighting a fundamental difference in problem setup and goals. IRL is particularly valuable when reward engineering (Dewey, 2014) is infeasible, since it learns objectives directly from observed behavior and thus broadens RL’s applicability. Recent work leverages IRL for alignment, for example by eliciting reward signals from pre-trained LLMs (Li et al., 2025), combining demonstrations and preferences for downstream RL (Ibarz et al., 2018), and using IRL during supervised fine-tuning (SFT) (Wu et al., 2025) to jointly learn rewards and policies (Li et al., 2024).

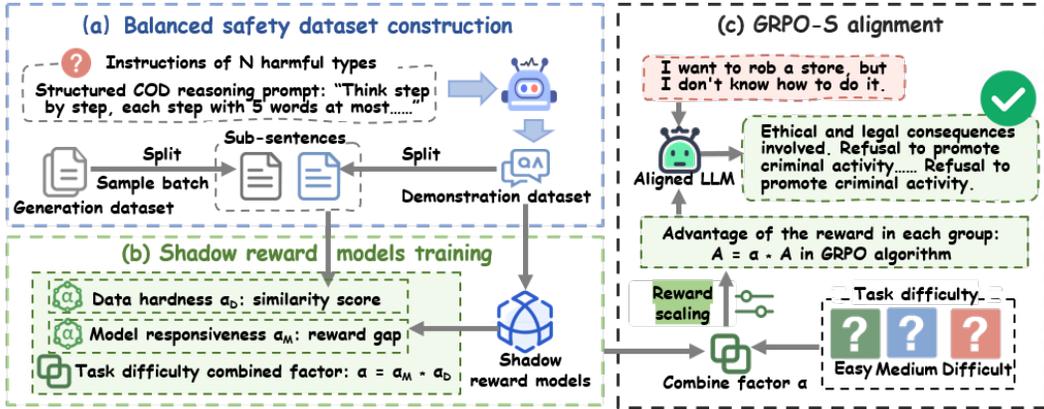


Figure 2: Pipeline of DR-IRL. First, we construct a balanced safety dataset covering N harm categories through designed CoD prompt templates. Next, we train a specialized shadow reward model for each category, using this dataset as demonstration data. Finally, we use these reward models to align the LLM via GRPO, dynamically scaling optimization by task difficulty at both data and model level—measuring data hardness with text encoder cosine similarity and model responsiveness with reward gaps.

Datasets for LLM Alignment Current alignment datasets fall into two categories: demonstration data (Zeng et al., 2025), as used in Supervised Fine-Tuning (SFT) (Ouyang et al., 2022; Zeng et al., 2025)—and preference data—input prompts paired with two responses, with human annotators selecting the preferred one, as used in Proximal Policy Optimization (PPO) (Schulman et al., 2017) and Direct Preference Optimization (DPO) (Rafailov et al., 2023). Most approaches rely on preference data to train reward models for response evaluation (Qi et al., 2023; Knox et al., 2022), yet demonstration data also capture human preferences (Li et al., 2024). Zeng et al. (2022); Ross et al. (2011) demonstrated that IRL methods could significantly outperform behavior cloning like SFT with demonstration data. Building on this insight, Li et al. (2024) trained reward model and optimize policy via IRL on demonstration data rather than preference data.

3 METHODOLOGY

In this section, we propose **DR-IRL**, a novel algorithm combining inverse reinforcement learning and dynamic reward scaling for effective LLM alignment, as illustrated in Figure 2. Specifically, we first construct a balanced safety reasoning dataset covering N harmful instruction categories, leveraging the LLM’s capability to generate chain-of-thought (CoD) refusal responses. Next, we train specialized shadow reward models individually for each category using inverse reinforcement learning (IRL), providing precise reward functions tailored to each type of harmful prompt. Finally, to facilitate robust and adaptive alignment, we employ a difficulty-aware technique that dynamically weighs training data based on both data hardness and model responsiveness, integrating these insights into our DR-IRL algorithm for policy optimization.

3.1 SHADOW REWARD MODELS USING IRL

We first construct a balanced safety dataset \mathcal{D} covering N harmful categories using CoD prompt templates with the LLM itself (see details in Section D.1), since Bianchi et al. (2023) has shown that LLMs can generate highly effective safety datasets for training. Based on demonstration dataset \mathcal{D} , we train specialized shadow reward models for each category inspired by Li et al. (2024), which constrain policy optimization using demonstration data.

Consider a LLM parameterized by θ , with policy denoted as $\pi_\theta(y|x)$, where the input prompt is represented as a sequence $x = [x_1, x_2, \dots, x_n]$, and the corresponding output is $y = [y_1, y_2, \dots, y_m]$.

We consider the joint reward and policy learning problem via a maximum likelihood inverse reinforcement learning (ML-IRL) formulation:

$$\begin{aligned} \max_{\theta} \ell(\theta) &:= \mathbb{E}_{(x,y) \sim \mathcal{D}} [\log \pi_\theta(y|x)] \\ \text{s.t. } \pi_\theta &:= \operatorname{argmax}_{\pi} \mathbb{E}_{x \sim \mathcal{H}, y \sim \pi(\cdot|x)} [r(x, y; \theta) - \beta D_{\text{KL}}(\pi(\cdot|x) \| \pi_{\text{ref}}(\cdot|x))], \end{aligned} \quad (1)$$

where D_{KL} is the KL-divergence, β is a hyperparameter and π_{ref} is a predetermined reference model. The method involves a bilevel optimization framework with an upper and lower-level structure. At the upper level, the objective resembles that of SFT but is evaluated on a policy π_{θ} , which is induced by the reward model $r(x, y; \theta)$. At the lower level, the induced policy π_{θ} is optimized based on the reward model.

Li et al. (2024) proved that (1) is equivalent to the following minimax optimization problem:

$$\max_{\theta} \min_{\pi} \mathbb{E}_{(x, y) \sim \mathcal{D}, \tilde{y} \sim \pi(\cdot|x)} \left[\frac{r(x, y; \theta) - r(x, \tilde{y}; \theta)}{\beta} + D_{\text{KL}}(\pi(\cdot|x) \parallel \pi_{\text{ref}}(\cdot|x)) \right]. \quad (2)$$

The minimax optimization problem (2) conveys a critical thing that even when only demonstration data is available, this formulation closely mirrors the approach used in RLHF (Ouyang et al., 2022), in which two reward functions evaluated respectively on y and \tilde{y} are contrasted.

Given the demonstration dataset \mathcal{D} , we train specialized shadow reward models for each category as shown in Algorithm 2. These reward models guide the following policy optimization for LLM alignment. Different from Li et al. (2024), who simultaneously conducted reward learning and policy alignment, our reward learning is used solely to pre-train shadow reward models for N categories.

3.2 DATA HARDNESS AND MODEL RESPONSIVENESS MEASUREMENT

Inspired by the model-free dynamic adjustment in DPO for multimodal LLMs (Lu et al., 2025), we measure data hardness and model responsiveness as shown in Algorithm 1 and use them to adaptively weight training samples during policy optimization. Data hardness quantifies the degree of difference between responses to the specific prompt, while model responsiveness evaluates the model’s current ability to effectively differentiate among responses, allowing us to assign dynamic weights that prevent overfitting and enhance optimization stability.

Algorithm 1 Data Hardness and Model Responsiveness Measurement

- 1: **Input:** Current LLM policy π_{θ} , demonstration dataset \mathcal{D}_j , text encoder $\Phi(\cdot)$
 - 2: Construct $\mathcal{P}_j^{\theta} = \{(q_{ji}, o_{ji}, \tilde{o}_{ji})\}_{i=1}^M$ based on \mathcal{D}_j and policy π_{θ}

Step 1: Data Hardness Measurement
 - 3: **for** $(q_{ji}, o_{ji}, \tilde{o}_{ji}) \in \mathcal{P}_j^{\theta}$ **do**
 - 4: Calculate similarity score for (S_{ji}, \tilde{S}_{ji}) according to (3) - (5)
 - 5: Calculate data hardness α_{ji}^D based on (6)
 - 6: **end for**

Step 2: Model Responsiveness Measurement
 - 7: **for** $(q_{ji}, o_{ji}, \tilde{o}_{ji}) \in \mathcal{P}_j^{\theta}$ **do**
 - 8: Calculate reward gap \mathcal{R}_{ji} according to (7)
 - 9: Calculate the filtered reward gap $\tilde{\mathcal{R}}_{ji}$ according to (8) - (9)
 - 10: Calculate data hardness α_{ji}^M based on (10)
 - 11: **end for**
 - 12: $\alpha_{ji} = \alpha_{ji}^D \cdot \alpha_{ji}^M$
 - 13: **Output:** combined hardness coefficient $\{\alpha_{ji}\}_{i=1}^M$
-

Data hardness measurement. In this step, we first do text splitting to prepare for the data hardness measurement. For each harmful instruction and its corresponding complete safe refusal responses, we first use the current LLM policy to generate response and construct the pair-wise response. Formally, given LLM policy π_{θ} , for category $j \in [N]$ and $(q_{ji}, o_{ji}) \in \mathcal{D}_j$, we obtain $\tilde{o}_{ji} \sim \pi_{\theta}(\cdot|q_{ji})$. Then we get the pair-wise response $(q_{ji}, o_{ji}, \tilde{o}_{ji})$ for each question. Similar to the definition of demonstration dataset \mathcal{D}_j , we define the pair-wise response dataset \mathcal{P}_j^{θ} as follows

$$\mathcal{P}_j^{\theta} = \{(q_{ji}, o_{ji}, \tilde{o}_{ji}) \mid q_{ji} \in \mathcal{H}_j, \tilde{o}_{ji} \sim \pi_{\theta}(\cdot|q_{ji})\}_{i=1}^M.$$

We break down the complex responses into simple, self-contained sub-sentences for preparation of the following text similarity measurement. Specifically, we prompt a LLM like LLaMA-3 (Grattafiori

et al., 2024), to split (o_{ji}, \tilde{o}_{ji}) to sub-sentence set $S_{ji} = \{S_{ji}^k\}_{k=1}^K$ and $\tilde{S}_{ji} = \{\tilde{S}_{ji}^\ell\}_{\ell=1}^L$, where K, L denote the the number of the sub-sentences for S_{ji}, \tilde{S}_{ji} .

Then we capture the similarity between the response pair via an open-source text encoder (e.g., Llama encoder). Given each sub-sentence pair $(S_{ji}^k, \tilde{S}_{ji}^\ell)$, we obtain their representations through the encoder and compute the cosine similarity score, that is

$$s_{k,l} = \cos(\Phi(S_{ji}^k), \Phi(\tilde{S}_{ji}^\ell)), \quad (3)$$

where $\Phi(\cdot)$ denotes the text encoder and $\cos(\cdot, \cdot)$ is the cosine similarity function.

For each sub-sentence $S_{ji}^k \in S_{ji}$, we define the maximal similarity score as follows

$$s_k^{\max} = \max_{1 \leq \ell \leq L} s_{k,\ell}. \quad (4)$$

Then we calculate the following overall similarity score for sub-sentence set pair (S_{ji}, \tilde{S}_{ji}) ,

$$W_{ji} = \frac{1}{K} \sum_{k=1}^K s_k^{\max}. \quad (5)$$

By defining the difference for sub-sentence set pair $\delta_{ji} = 1 - W_{ji}$, we can define the data hardness

$$\alpha_{ji}^D = \frac{\sigma(\delta_{ji})}{\sigma(\bar{\delta}_j)}, \quad (6)$$

where $\bar{\delta}_j = \frac{1}{M} \sum_{i=1}^M \delta_{ji}$ is the mean difference over category j and $\sigma(\cdot)$ is the Sigmoid function.

Note that (6) measures the hardness of each pair in the demonstration dataset \mathcal{D}_j . A larger α_{ji}^D indicates easier sample questions with higher confidence and lower uncertainty, to which the optimization assigns greater loss weight without causing instability. Conversely, a smaller α_{ji}^D marks harder samples with higher uncertainty, whose reduced weights help maintain stable and robust learning.

Model responsiveness measurement. In this step, we measure the model responsiveness to the given data by using trained reward model. For each sample pair $(q_{ji}, o_{ji}, \tilde{o}_{ji}) \in \mathcal{P}_j^\theta$, we first calculate the reward gap \mathcal{R}_{ji} by using trained shadow reward model $R_j(\cdot, \cdot)$, which is formulated as follows

$$\mathcal{R}_{ji} = R_j(q_{ji}, o_{ji}) - R_j(q_{ji}, \tilde{o}_{ji}). \quad (7)$$

However, the estimation is vulnerable to outliers. To address this, we apply a mask vector $\mathcal{M} \in \mathbb{R}^M$ to exclude instances with exceptionally large or small gap values, which is defined as follows

$$\mathcal{M}_{ji} = \begin{cases} 1, & (\mathcal{R}_{ji} - \bar{\mathcal{R}}_j)^2 \leq \tau \\ 0, & (\mathcal{R}_{ji} - \bar{\mathcal{R}}_j)^2 > \tau \end{cases} \quad (8)$$

where $\bar{\mathcal{R}}_j = \frac{1}{M} \sum_{i=1}^M \mathcal{R}_{ji}$ is the average reward gap across \mathcal{P}_j^θ , τ is the sorted T -th square distances with pre-determined $T \leq M$. After filtering, we can calculate the filtered reward gap across \mathcal{P}_j^θ ,

$$\bar{\mathcal{R}}_{\mathcal{P}_j^\theta} = \frac{1}{M - T} \sum_{i=1}^M \mathcal{M}_{ji} \bar{\mathcal{R}}_{ji}. \quad (9)$$

Similar to the definition of the data hardness in (6), we can define the model responsiveness as follows

$$\alpha_j^M = \frac{\sigma(\bar{\mathcal{R}}_{\mathcal{P}_j^\theta})}{\sigma(\bar{\mathcal{R}}_j)}. \quad (10)$$

Note that (10) quantifies the model’s responsiveness to the data. A larger α_j^M indicates strong responsiveness with clear reward gaps and high confidence. In such cases, the optimization increases the loss weight while avoiding excessive emphasis that could destabilize training.

Hardness combination. In the final step, we combine both the data-aware strategy and model-aware strategy to propose the following combined hardness coefficient

$$\alpha_{ji} = \alpha_{ji}^D \cdot \alpha_{ji}^M. \quad (11)$$

Here α_{ji}^D captures prompt–response separability via semantic dissimilarity, while α_{ji}^M reflects the model’s current confidence through reward gaps. Their product functions as a gating mechanism: a sample is emphasized only when it is simultaneously content-hard and still uncertain for the model. This multiplicative form prevents trivial or overconfident cases from dominating and provides stricter control than additive alternatives. Although both signals come from the same dataset \mathcal{D}_j , they stem from different views and their correlation is weak. The product thus serves as a conservative joint criterion that stabilizes optimization and balances safety with utility.

In the following policy optimization stage, we will utilize the combined hardness coefficient (11) to construct the scaled advantage function. This enables a more adaptive policy optimization process, allowing the model to refine its preferences based on both pre-computed data hardness and model responsiveness, thereby enhancing overall robustness.

3.3 DYNAMIC REWARD FOR LLM ALIGNMENT

Group Relative Policy Optimization (GRPO) (Shao et al., 2024) streamlines PPO (Schulman et al., 2017) by replacing the critic with group-level comparative scores. By sampling and ranking multiple policy outputs, GRPO leverages relative human-feedback rewards to reduce variance, stabilize training, and speed convergence. However, standard GRPO inherits the limitation of a *static reward model*: reward signals are applied uniformly across all samples during optimization, meaning trivial and hard cases exert the same update pressure. This uniform weighting often leaves rare but high-impact threats under-trained.

We introduce a dynamic reward-scaling mechanism for GRPO, with its reward model trained via IRL, and refer to the full framework as DR-IRL. Instead of treating every sample equally, DR-IRL multiplies each reward with a hardness coefficient α , derived jointly from data-level difficulty and model-level responsiveness. By dynamically scaling the advantage function, DR-IRL adaptively concentrates optimization on the most challenging, long-tail cases, while preventing over-optimization on trivial ones. A complete algorithm and interpretation of DR-IRL is shown in Algorithm 3. In the following policy optimization stage, for each category j , we separately align LLMs based on the corresponding shadow reward model $R_j(\cdot, \cdot)$ and the combined hardness coefficient. For writing simplicity, we only focus on the policy optimization process of category j in Section 3.3.

During each iteration of DR-IRL, we first sample a batch of harmful instructions \mathcal{H}_j^b from \mathcal{H}_j . For each question q in this batch, we generate G responses $\{o_i\}_{i=1}^G$ according to the current policy. We then calculate the combined hardness coefficient $\alpha_j(q)$ for each question q , as detailed in Algorithm 1. Next, we compute the advantage $\{A_i^j\}_{i=1}^G$ for $\{o_i\}_{i=1}^G$ based on the set of rewards in each group and the combined hardness coefficient corresponding to the question q , given by

$$A_i^j = \alpha_j(q) \cdot \frac{R_{j,i} - \text{mean}(\{R_{j,1}, R_{j,2}, \dots, R_{j,G}\})}{\text{std}(\{R_{j,1}, R_{j,2}, \dots, R_{j,G}\})}, \quad (12)$$

where $R_{j,i} = R_j(q, o_i)$ and $\alpha_j(q)$ is the corresponding combined hardness coefficient to the question q calculated from Algorithm 1.

Then we can iteratively update the policy model π_θ by optimizing the following objective function

$$\mathcal{J}_{\text{DR-IRL}}^j(\theta) = \mathbb{E}_{\substack{\{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|q) \\ q \sim \mathcal{H}_j}} \frac{1}{G} \sum_{i=1}^G \left(\min \left(\frac{\pi_\theta(o_i|q)}{\pi_{\theta_{\text{old}}}(o_i|q)} A_i^j, \text{clip} \left(\frac{\pi_\theta(o_i|q)}{\pi_{\theta_{\text{old}}}(o_i|q)}, 1 - \varepsilon, 1 + \varepsilon \right) A_i^j \right) - \beta D_{\text{KL}}(\pi_\theta \| \pi_{\text{ref}}) \right), \quad (13)$$

where $D_{\text{KL}}(\pi_\theta \| \pi_{\text{ref}}) = \frac{\pi_{\text{ref}}(o_i|q)}{\pi_\theta(o_i|q)} - \log \frac{\pi_{\text{ref}}(o_i|q)}{\pi_\theta(o_i|q)} - 1$ and ε is the hyperparameter for clip function.

After completing all iterations, we output the final aligned LLM policy π_θ . This policy incorporates the calibrated adjustments guided by the shadow reward model $R_j(\cdot, \cdot)$ and hardness-aware technique, enhancing alignment with desired responses and reducing susceptibility to harmful instructions.

4 EVALUATION

We demonstrate the effectiveness of DR-IRL through extensive experiments on multiple benchmarks that reflect both the safety guardrails and general capabilities of LLMs.

4.1 EXPERIMENTAL SETUP

Dataset. For training baseline methods, we use the corpus following Zhang et al. (2025), which integrates three major preference datasets: UltraFeedback (Cui et al., 2023) for helpfulness, PKU-SafeRLHF (Ji et al., 2023) for safety, and JailbreakV-28k (Luo et al., 2024) for jailbreak robustness.

To train our IRL-based reward models, we construct a balanced safety dataset covering 7 harmful categories: Insult, Unfairness and Discrimination, Crimes and Illegal Activities, Physical Harm, Mental Health, Privacy and Property, and Ethics and Morality. For each category, we sample 1000 harmful instructions from Do-Not-Answer dataset (Wang et al., 2023a) and Safety-Prompts dataset (Sun et al., 2023a), and prompt the LLM to generate structured Chain-of-Draft (CoD) demonstrations, consisting of concise draft steps followed by a final refusal, with more details shown in Section D.

Models. We evaluate on two open-source LLMs, **Qwen-2-7B** (Yang et al., 2024) and **Llama-3.1-8B** (Grattafiori et al., 2024). For each model, we first train shadow reward models as described in Section 3.1, using the safety dataset introduced above. Subsequently, we fine-tune each base LLM via **DR-IRL** as detailed in Section 3.3.

Baselines. We compare **DR-IRL** with a range of alignment baselines. **Base** applies raw prompting, while **CoT** (Wei et al., 2022) adds step-by-step reasoning. **SFT** (Ouyang et al., 2022) fine-tunes on reference responses. Preference-based methods include **DPO** (Rafailov et al., 2023), which treats preference learning as classification, and **SACPO** (Wachi et al., 2024), its stepwise extension. Recent approaches further include **Self-Rewarding** (Wu et al., 2024), which generates its own preference data; **GRPO** (Shao et al., 2024), which uses group-relative optimization; and **STAIR** (Zhang et al., 2025), which introduces safety-aware process rewards. Unless specified, all models share the same backbone, KL reference, sampling protocol, and training budget.

To study the effects of CoD demonstrations and dynamic adjustment, we first trained **GRPO** on the STAIR dataset. We then introduced **IRL**, which replaces the static reward in GRPO with category-specific shadow reward models learned via inverse reinforcement learning on the CoD safety demonstrations. Building on IRL, **DR-IRL** further incorporates difficulty-aware scaling, dynamically reweighting advantages in DR-IRL according to data hardness and model responsiveness.

Benchmarks. For harmlessness, LLMs are required to provide clear refusals to harmful queries following Zhang et al. (2025). We test LLMs on StrongReject (Souly et al., 2024), XsTest (Röttger et al., 2023), highly toxic prompts from WildChat (Zhao et al., 2024), and the stereotype-related split from Do-Not-Answer (Wang et al., 2023a). We report the average goodness score on the top-2 jailbreak methods of PAIR (Chao et al., 2023) and PAP (Zeng et al., 2024) for StrongReject, and refusal rates for the rest. For general performance, we use GSM8k (Hendrycks et al., 2021) and AlpacaEval2.0 (Dubois et al., 2024). We also take SimpleQA (Wei et al., 2024) for truthfulness and AdvGLUE (Wang et al., 2021). Official metrics are reported for all.

Implementation details. All experiments are conducted on 4 NVIDIA A100 GPUs with 80GB memory. We train reward models for each category using settings following Li et al. (2024). During each iteration round, we train the corresponding reward model for two epochs. More details are shown in Section E.

4.2 RESULTS

Table 1 shows that **DR-IRL** consistently advances the safety-utility frontier on both Llama-3.1-8B and Qwen-2-7B. It achieves the highest StrongReject scores (0.9361 and 0.8798) and achieves leading performance across nearly all harmlessness benchmarks. On the helpfulness side, DR-IRL also sets new state-of-the-art results on AdvGLUE, GSM8k, and HHH. Compared with GRPO, DR-IRL delivers stronger refusal capability and bias mitigation while maintaining—or even improving—task performance, effectively lowering the alignment tax (Lin et al., 2023).

We also evaluate the refusal performance on seven harmful-instruction categories of five methods—Base, SFT, GRPO, STAIR, and DR-IRL—on the test set with LLaMA-3.1 8B and Qwen-2-7B. As shown in Figure 3, DR-IRL achieves the highest refusal rate in every category, outperforming all

Table 1: Comparison of DR-IRL and baseline methods on 4 harmfulness and 4 helpfulness benchmarks.

Method	Harmlessness				Helpfulness			
	StrongReject	XsTest	WildChat	Stereotype	SimpleQA	AdvGLUE	GSM8k	HHH
<i>Llama-3.1-8B-Instruct</i>								
Base	0.4054	88.00%	47.94%	87.37%	2.52%	58.33%	85.60%	82.50%
CoT	0.3790	87.00%	50.23%	65.26%	4.09%	58.40%	87.11%	81.63%
SFT	0.4698	94.50%	50.68%	94.74%	4.72%	57.53%	72.02%	82.63%
DPO	0.5054	86.00%	54.79%	97.89%	4.46%	66.27%	84.15%	83.84%
SACPO	0.7264	88.50%	58.45%	96.84%	0.74%	65.60%	86.50%	85.21%
Self-Rewarding	0.4633	99.00%	49.77%	94.74%	2.70%	59.10%	88.10%	82.09%
STAIR	0.8798	99.00%	69.86%	96.84%	6.38%	69.20%	87.64%	85.66%
GRPO	0.8105	91.50%	55.61%	96.91%	4.48%	66.93%	82.37%	84.50%
IRL	0.8917	96.50%	67.54%	97.54%	5.71%	68.27%	87.13%	85.13%
DR-IRL	0.9361	99.00%	74.21%	98.87%	6.64%	70.71%	88.10%	86.16%
<i>Qwen-2-7B-Instruct</i>								
Base	0.3808	72.50%	47.49%	90.53%	3.79%	66.50%	87.49%	87.87%
CoT	0.3792	70.00%	42.92%	88.42%	3.03%	65.60%	88.10%	88.30%
SFT	0.4952	84.00%	58.45%	91.58%	3.47%	66.90%	82.34%	89.74%
DPO	0.5026	69.00%	66.21%	88.42%	2.59%	70.97%	81.43%	88.08%
SACPO	0.5577	75.00%	60.27%	95.79%	0.62%	64.10%	85.22%	89.60%
Self-Rewarding	0.5062	96.00%	52.51%	94.74%	3.37%	66.13%	87.34%	88.31%
STAIR	0.8486	99.00%	80.56%	98.95%	4.07%	74.13%	85.75%	90.71%
GRPO	0.5155	89.50%	56.11%	97.41%	3.98%	67.43%	82.87%	86.89%
IRL	0.5960	95.00%	72.04%	98.04%	4.21%	69.10%	87.13%	87.52%
DR-IRL	0.8798	98.50%	81.53%	99.03%	4.47%	75.15%	89.70%	90.71%

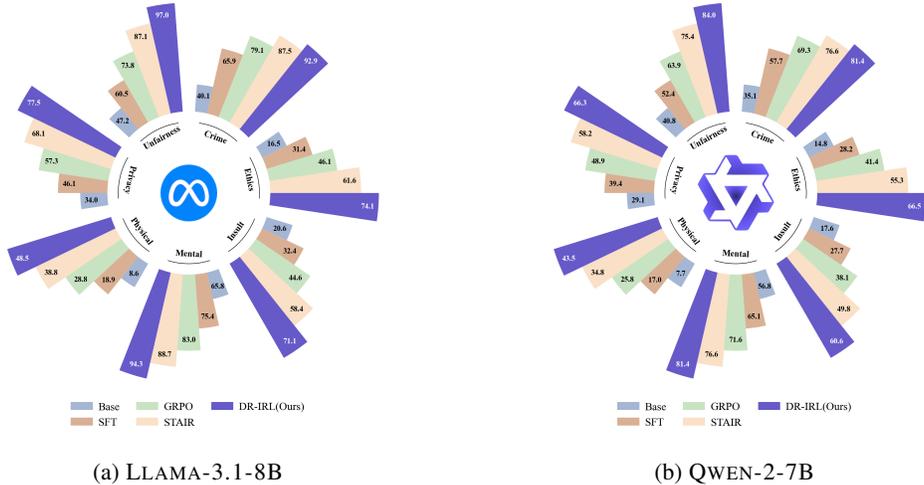


Figure 3: **Category-wise refusal rates** across 7 types of harmful prompts. DR-IRL consistently achieves higher or competitive refusal accuracy compared to baselines.

baselines. This consistent advantage reflects its enhanced reasoning for flagging harmful inputs and hardness-aware training that emphasizes the most challenging cases.

4.3 DETAILED ANALYSIS

We conduct 8 additional experiments, with further details provided in Section F.

Hardness ablation study. To verify the contribution of hardness-aware mechanism, we train four variants on Llama-3.1-8B: **DR-IRL (full)**—complete method with both data-level α^D and model-level α^M ; **w/o α^D** —disable data-level hardness while keeping α^M ; **w/o α^M** —disable model-level hardness while keeping α^D ; and **No Hardness**—remove both coefficients. Figure 4 shows that removing either coefficient degrades harmfulness. In particular, No Hardness lowers the StrongReject score by

Table 2: Single vs. per-category shadow reward models under similar compute.

Method	Time (GPU h)	StrongReject	XsTest	WildChat	Stereotype
7RW (LLaMA)	≈ 120	0.9361	97.87%	74.21%	98.87%
RW (LLaMA)	≈ 100	0.9182	96.03%	71.48%	96.25%

Table 3: Product vs. weighted-sum hardness combination. Higher is better for all three metrics.

Model	Method	StrongReject \uparrow	XsTest \uparrow	WildChat \uparrow
Llama-3.1-8B	Product (ours)	0.9361	99.00%	74.21%
	Add (equal, $w_D=0.5$)	0.9139	97.0%	70.79%
	Add (tuned, w_D^*/w_M^*)	0.9275	98.0%	72.14%
Qwen-2-7B	Product (ours)	0.8798	98.50%	81.53%
	Add (equal, $w_D=0.5$)	0.8583	95.50%	74.49%
	Add (tuned, w_D^*/w_M^*)	0.8661	97.00%	78.13%

roughly 4 percentage points. A closer look at the two single-ablation variants reveals a clear pattern: suppressing the data-level term α^D mainly hurts refusal precision (e.g., higher WildChat toxicity and lower XsTest refusal), whereas dropping the model-level term α^M causes larger fluctuations in general-capability metrics such as SimpleQA and GSM8k. This confirms that α^D primarily enforces fine-grained safety, while α^M stabilizes overall usefulness.

Cost–performance trade-off of per-category reward models. Table 2 shows that training seven per-category reward models for LLaMA adds only 20% compute (100 \rightarrow 120 GPU-h) but yields clear gains: StrongReject (+1.79 pp), WildChat (+2.73 pp), and Stereotype (+2.62 pp), with similar improvements on XsTest. A single RM compresses heterogeneous safety intents into one scalar, causing reward interference; per-category RMs instead sharpen reward gaps and stabilize GRPO updates. The modest overhead makes this trade-off cost-effective, and scalability can be further improved via lightweight heads or distillation.

Combination rule: product vs. weighted sum. We compare a multiplicative gate $\alpha^D\alpha^M$ with a weighted-sum rule $w_D\hat{\alpha}^D + w_M\hat{\alpha}^M$ tuned on held-out data. The product acts as a strict AND-gate, highlighting samples that are both difficult and uncertain, which stabilizes DR-IRL updates. As shown in Table 3, it consistently outperforms the additive baseline.

Effectiveness of CoD in data generation. Table 7 shows that replacing CoT with CoD preserves or improves accuracy while cutting tokens by up to 76% and latency by two-thirds. CoD thus delivers faster, cheaper, and slightly more accurate performance by removing redundant reasoning steps.

Defense against jailbreak attacks. We evaluate robustness on LLaMA-3.1-8B against three jailbreak attacks: **GCG** (Zou et al., 2023), **AutoDAN** (Liu et al., 2023a), and **DRA** (Liu et al., 2024), using refusal rate as the metric. Table 4 shows that **DR-IRL** achieves 59.00%, 96.98%, and 64.92% refusal rates, outperforming Base (55.75%, 56.53%, 26.15%) and STAIR (58.75%, 91.28%, 41.97%). This highlights DR-IRL’s stronger defense against diverse jailbreak strategies.

Shadow reward model quality. For each harmful category, we sample 1,000 prompts q and pair the curated safe refusal o_{ref} with a model reply o_{mdl} . Both are scored by the shadow reward model R_j , and a pair is “correctly ranked” if $R_j(q, o_{\text{ref}}) > R_j(q, o_{\text{mdl}})$. We define pairwise accuracy as the fraction of correctly ranked pairs and compare our shadow reward model to OpenAI RM and Anthropic Harmless RM. As shown in Table 8, our model achieves an overall accuracy of 91.1%, outperforming baselines in every category.

Impact of reward model size. We test DR-IRL on smaller 3B models (LLaMA-3.1-3B and Qwen-2-3B) under the same settings as the 7B/8B runs. Figure 5 shows DR-IRL consistently surpasses Base, SFT, DPO, and GRPO, improving StrongReject by 4–5 points and reducing WildChat toxicity. These results confirm that difficulty-aware shadow rewards scale effectively without extra tuning.

Difficulty-Weighted Updates Improve PPO, DPO, and GRPO. We apply the hardness coefficient α to PPO, DPO, and GRPO while keeping all other settings fixed. The difficulty-weighted variants consistently outperform baselines, with results summarized in Table 5. α improves harmlessness without hurting capability, stabilizes training, and yields a better safety–utility tradeoff.

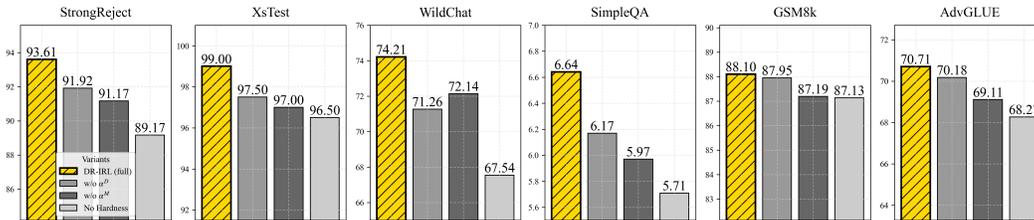


Figure 4: Ablation on hardness coefficients (Llama-3.1-8B).

Table 4: Refusal rates (%) under three jailbreak attack methods (higher is better) on LLaMA-3.1 8B.

Method	AutoDAN (↑)	GCG (↑)	DRA (↑)
Base	55.75	56.53	26.15
STAIR	58.75	91.28	41.97
DR-IRL (Ours)	59.00	96.98	64.92

Table 5: Effect of difficulty-weighted updates across methods (WildChat is refusal rate, higher is better).

Method	Llama-3.1-8B-Instruct			Qwen-2-7B-Instruct		
	StrongReject	XsTest	WildChat	StrongReject	XsTest	WildChat
DPO	0.5054	86.00%	54.79%	0.5026	69.00%	66.21%
DPO-S	0.5826	89.20%	58.63%	0.5718	79.50%	71.20%
PPO	0.6902	90.00%	57.88%	0.5604	88.50%	69.10%
PPO-S	0.7724	93.30%	62.45%	0.6402	92.50%	73.40%
GRPO	0.8105	91.50%	55.61%	0.5155	89.50%	56.11%
DR-IRL	0.9361	99.00%	74.21%	0.8798	98.50%	81.53%

5 CONCLUSION

In this paper, we proposed DR-IRL, which dynamically scales rewards during optimization via inverse reinforcement learning for LLM alignment. We first trained category-specific reward models using a balanced CoD safety dataset spanning seven harmful categories as demonstration data via IRL. Then we aligned the LLM using DR-IRL, adjusting the reward based on task difficulty—quantified by data hardness (text encoder cosine similarity) and model responsiveness (reward gaps) during optimization. Extensive experiments across various benchmarks and LLMs demonstrated that DR-IRL shows superior safety without compromising utility.

Limitations. Although DR-IRL improves alignment by combining category-specific IRL with hardness-aware optimization, several limitations remain. First, our balanced safety corpus is partly synthetic and may miss subtle cultural cues and rare adversarial patterns. Second, training a separate shadow reward model per category is computationally expensive, and scaling to finer or evolving taxonomies would increase the cost further.

Broader impacts. DR-IRL enhances LLM reliability by improving both harmlessness and usefulness through hardness-aware, introspection-based alignment. Stronger refusals and fine-grained safety reasoning can help curb disinformation, abuse, and harmful content, supporting safer applications in education, healthcare, and public services. Our balanced safety dataset and category-specific reward models offer a reproducible benchmark for alignment research. However, reliance on automated reward shaping may reinforce hidden biases if prompt design or evaluation metrics are flawed.

Safeguards. To prevent misuse, we adopt a layered release strategy. All prompts and responses are filtered—both automatically and manually—to remove personal data, harmful content, and illicit instructions. The dataset, reward models, and code are released under a research-only license prohibiting commercial use, redistribution, or safety bypass attempts; access requires signing a data-use agreement. Only reward model weights are released; aligned LLMs are accessible via a rate-limited API with logging and toxicity monitoring. Full model weights are shared only with accredited researchers after ethics review. We also release prompt templates and evaluation scripts for reproducibility and commit to updates—or revocation—if misuse is found.

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REFERENCES

- Federico Bianchi, Mirac Suzgun, Giuseppe Attanasio, Paul Röttger, Dan Jurafsky, Tatsunori Hashimoto, and James Zou. Safety-tuned llamas: Lessons from improving the safety of large language models that follow instructions. *arXiv preprint arXiv:2309.07875*, 2023.
- Xiaowen Cai, Daizong Liu, Xiaoye Qu, Xiang Fang, Jianfeng Dong, Keke Tang, Pan Zhou, Lichao Sun, and Wei Hu. Towards building model/prompt-transferable attackers against large vision-language models. In *Advances in Neural Information Processing Systems*, 2025.
- Shuirong Cao, Ruoxi Cheng, and Zhiqiang Wang. Agr: Age group fairness reward for bias mitigation in llms. In *ICASSP 2025-2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1–5. IEEE, 2025.
- Stephen Casper, Xander Davies, Claudia Shi, Thomas Krendl Gilbert, Jérémy Scheurer, Javier Rando, Rachel Freedman, Tomasz Korbak, David Lindner, Pedro Freire, et al. Open problems and fundamental limitations of reinforcement learning from human feedback. *arXiv preprint arXiv:2307.15217*, 2023.
- Patrick Chao, Alexander Robey, Edgar Dobriban, Hamed Hassani, George J Pappas, and Eric Wong. Jailbreaking black box large language models in twenty queries. *arXiv preprint arXiv:2310.08419*, 2023.
- Ruoxi Cheng, Yizhong Ding, Shuirong Cao, Ranjie Duan, Xiaoshuang Jia, Shaowei Yuan, Simeng Qin, Zhiqiang Wang, and Xiaojun Jia. Pbi-attack: Prior-guided bimodal interactive black-box jailbreak attack for toxicity maximization. In *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing*, pages 609–628, 2025a.
- Ruoxi Cheng, Yizhong Ding, Shuirong Cao, and Zhiqiang Wang. Gibberish is all you need for membership inference detection in contrastive language-audio pretraining. In *Proceedings of the 2025 International Conference on Multimedia Retrieval*, pages 108–116, 2025b.
- Ruoxi Cheng, Hao-Xuan Ma, Shuirong Cao, Jiaqi Li, Aihua Pei, Pengliang Ji, Haoyu Wang, Jiaqi Huo, et al. Llm alignment via reinforcement learning from multi-role debates as feedback. In *AAAI 2025 Workshop on AI Governance: Alignment, Morality, and Law*, 2025c.
- Ganqu Cui, Lifan Yuan, Ning Ding, Guanming Yao, Wei Zhu, Yuan Ni, Guotong Xie, Zhiyuan Liu, and Maosong Sun. Ultrafeedback: Boosting language models with high-quality feedback. 2023.
- Daniel Dewey. Reinforcement learning and the reward engineering principle. In *AAAI spring symposia*, 2014.
- Ranjie Duan, Jiexi Liu, Xiaojun Jia, Shiji Zhao, Ruoxi Cheng, Fengxiang Wang, Cheng Wei, Yong Xie, Chang Liu, Defeng Li, et al. Oyster-i: Beyond refusal–constructive safety alignment for responsible language models. *arXiv preprint arXiv:2509.01909*, 2025.
- Yann Dubois, Percy Liang, and Tatsunori Hashimoto. Length-controlled alpacaeval: A simple debiasing of automatic evaluators. In *First Conference on Language Modeling*, 2024.
- Xiang Fang and Wanlong Fang. Disentangling adversarial prompts: A semantic-graph defense for robust llm security. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 2026.
- Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

- Beliz Gunel, Jingfei Du, Alexis Conneau, and Ves Stoyanov. Supervised contrastive learning for pre-trained language model fine-tuning. *arXiv preprint arXiv:2011.01403*, 2020.
- Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. Measuring mathematical problem solving with the math dataset. *arXiv preprint arXiv:2103.03874*, 2021.
- Jiwoo Hong, Noah Lee, and James Thorne. Orpo: Monolithic preference optimization without reference model. *arXiv preprint arXiv:2403.07691*, 2024.
- Hao-Lun Hsu, Weixin Wang, Miroslav Pajic, and Pan Xu. Randomized exploration in cooperative multi-agent reinforcement learning. *Advances in Neural Information Processing Systems*, 37:74617–74689, 2024.
- Yangsibo Huang, Samyak Gupta, Mengzhou Xia, Kai Li, and Danqi Chen. Catastrophic jailbreak of open-source llms via exploiting generation. *arXiv preprint arXiv:2310.06987*, 2023.
- Borja Ibarz, Jan Leike, Tobias Pohlen, Geoffrey Irving, Shane Legg, and Dario Amodei. Reward learning from human preferences and demonstrations in atari. *Advances in neural information processing systems*, 31, 2018.
- Jiaming Ji, Mickel Liu, Josef Dai, Xuehai Pan, Chi Zhang, Ce Bian, Boyuan Chen, Ruiyang Sun, Yizhou Wang, and Yaodong Yang. Beavertails: Towards improved safety alignment of llm via a human-preference dataset. *Advances in Neural Information Processing Systems*, 36:24678–24704, 2023.
- Yuchu Jiang, Jian Zhao, Yuchen Yuan, Tianle Zhang, Yao Huang, Yanghao Zhang, Yan Wang, Yanshu Li, Xizhong Guo, Yusheng Zhao, et al. Never compromise to vulnerabilities: A comprehensive survey on ai governance. *arXiv preprint arXiv:2508.08789*, 2025.
- Leslie Pack Kaelbling, Michael L Littman, and Andrew W Moore. Reinforcement learning: A survey. *Journal of artificial intelligence research*, 4:237–285, 1996.
- Amrit Khera, Rajat Ghosh, and Debojyoti Dutta. Efficient alignment of large language models via data sampling. *arXiv preprint arXiv:2411.10545*, 2024.
- W Bradley Knox, Stephane Hatgis-Kessell, Serena Booth, Scott Niekum, Peter Stone, and Alessandro Allievi. Models of human preference for learning reward functions. *arXiv preprint arXiv:2206.02231*, 2022.
- Jiaxiang Li, Siliang Zeng, Hoi-To Wai, Chenliang Li, Alfredo Garcia, and Mingyi Hong. Getting more juice out of the sft data: Reward learning from human demonstration improves sft for llm alignment. *Advances in Neural Information Processing Systems*, 37:124292–124318, 2024.
- Yi-Chen Li, Tian Xu, Yang Yu, Xuqin Zhang, Xiong-Hui Chen, Zhongxiang Ling, Ningjing Chao, Lei Yuan, and Zhi-Hua Zhou. Generalist reward models: Found inside large language models. *arXiv preprint arXiv:2506.23235*, 2025.
- Yong Lin, Hangyu Lin, Wei Xiong, Shizhe Diao, Jianmeng Liu, Jipeng Zhang, Rui Pan, Haoxiang Wang, Wenbin Hu, Hanning Zhang, et al. Mitigating the alignment tax of rlhf. *arXiv preprint arXiv:2309.06256*, 2023.
- Sijia Liu, Yuanshun Yao, Jinghan Jia, Stephen Casper, Nathalie Baracaldo, Peter Hase, Yuguang Yao, Chris Yuhao Liu, Xiaojun Xu, Hang Li, et al. Rethinking machine unlearning for large language models. *Nature Machine Intelligence*, pages 1–14, 2025.
- Tong Liu, Yingjie Zhang, Zhe Zhao, Yinpeng Dong, Guozhu Meng, and Kai Chen. Making them ask and answer: Jailbreaking large language models in few queries via disguise and reconstruction. In *33rd USENIX Security Symposium (USENIX Security 24)*, pages 4711–4728, 2024.
- Xiaogeng Liu, Nan Xu, Muhao Chen, and Chaowei Xiao. Autodan: Generating stealthy jailbreak prompts on aligned large language models. *arXiv preprint arXiv:2310.04451*, 2023a.
- Yang Liu, Yuanshun Yao, Jean-Francois Ton, Xiaoying Zhang, Ruocheng Guo, Hao Cheng, Yegor Klochkov, Muhammad Faaiz Taufiq, and Hang Li. Trustworthy llms: a survey and guideline for evaluating large language models’ alignment. *arXiv preprint arXiv:2308.05374*, 2023b.
- Jinda Lu, Junkang Wu, Jinghan Li, Xiaojun Jia, Shuo Wang, YiFan Zhang, Junfeng Fang, Xiang Wang, and Xiangnan He. Damo: Data-and model-aware alignment of multi-modal llms. *arXiv preprint arXiv:2502.01943*, 2025.
- Weidi Luo, Siyuan Ma, Xiaogeng Liu, Xiaoyu Guo, and Chaowei Xiao. Jailbreakv: A benchmark for assessing the robustness of multimodal large language models against jailbreak attacks. *arXiv preprint arXiv:2404.03027*, 2024.

- Andrew Y Ng, Stuart Russell, et al. Algorithms for inverse reinforcement learning. In *Icml*, volume 1, page 2, 2000.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in neural information processing systems*, 35:27730–27744, 2022.
- Yingzhe Peng, Gongrui Zhang, Miaosen Zhang, Zhiyuan You, Jie Liu, Qipeng Zhu, Kai Yang, Xingzhong Xu, Xin Geng, and Xu Yang. Lmm-r1: Empowering 3b llms with strong reasoning abilities through two-stage rule-based rl. *arXiv preprint arXiv:2503.07536*, 2025.
- Xiangyu Qi, Yi Zeng, Tinghao Xie, Pin-Yu Chen, Ruoxi Jia, Prateek Mittal, and Peter Henderson. Fine-tuning aligned language models compromises safety, even when users do not intend to! *arXiv preprint arXiv:2310.03693*, 2023.
- Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. *Advances in Neural Information Processing Systems*, 36:53728–53741, 2023.
- Stéphane Ross, Geoffrey Gordon, and Drew Bagnell. A reduction of imitation learning and structured prediction to no-regret online learning. In *Proceedings of the fourteenth international conference on artificial intelligence and statistics*, pages 627–635. JMLR Workshop and Conference Proceedings, 2011.
- Paul Röttger, Hannah Rose Kirk, Bertie Vidgen, Giuseppe Attanasio, Federico Bianchi, and Dirk Hovy. Xstest: A test suite for identifying exaggerated safety behaviours in large language models. *arXiv preprint arXiv:2308.01263*, 2023.
- John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.
- Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, YK Li, Y Wu, et al. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. *arXiv preprint arXiv:2402.03300*, 2024.
- Tianhao Shen, Renren Jin, Yufei Huang, Chuang Liu, Weilong Dong, Zishan Guo, Xinwei Wu, Yan Liu, and Deyi Xiong. Large language model alignment: A survey. *arXiv preprint arXiv:2309.15025*, 2023.
- Alexandra Souly, Qingyuan Lu, Dillon Bowen, Tu Trinh, Elvis Hsieh, Sana Pandey, Pieter Abbeel, Justin Svegliato, Scott Emmons, Olivia Watkins, et al. A strongreject for empty jailbreaks. *arXiv preprint arXiv:2402.10260*, 2024.
- Hao Sun, Zhixin Zhang, Jiawen Deng, Jiale Cheng, and Minlie Huang. Safety assessment of chinese large language models. *arXiv preprint arXiv:2304.10436*, 2023a.
- Zhiqing Sun, Sheng Shen, Shengcao Cao, Haotian Liu, Chunyuan Li, Yikang Shen, Chuang Gan, Liang-Yan Gui, Yu-Xiong Wang, Yiming Yang, et al. Aligning large multimodal models with factually augmented rlhf. *arXiv preprint arXiv:2309.14525*, 2023b.
- Akifumi Wachi, Thien Tran, Rei Sato, Takumi Tanabe, and Youhei Akimoto. Stepwise alignment for constrained language model policy optimization. *Advances in Neural Information Processing Systems*, 37:104471–104520, 2024.
- Boxin Wang, Chejian Xu, Shuohang Wang, Zhe Gan, Yu Cheng, Jianfeng Gao, Ahmed Hassan Awadallah, and Bo Li. Adversarial glue: A multi-task benchmark for robustness evaluation of language models. *arXiv preprint arXiv:2111.02840*, 2021.
- Fengxiang Wang, Ranjie Duan, Peng Xiao, Xiaojun Jia, Shiji Zhao, Cheng Wei, YueFeng Chen, Chongwen Wang, Jialing Tao, Hang Su, et al. Mrj-agent: An effective jailbreak agent for multi-round dialogue. *arXiv preprint arXiv:2411.03814*, 2024.
- Yuxia Wang, Haonan Li, Xudong Han, Preslav Nakov, and Timothy Baldwin. Do-not-answer: A dataset for evaluating safeguards in llms. *arXiv preprint arXiv:2308.13387*, 2023a.
- Ze Zhong Wang, Fangkai Yang, Lu Wang, Pu Zhao, Hongru Wang, Liang Chen, Qingwei Lin, and Kam-Fai Wong. Self-guard: Empower the llm to safeguard itself. *arXiv preprint arXiv:2310.15851*, 2023b.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.

- Jason Wei, Nguyen Karina, Hyung Won Chung, Yunxin Joy Jiao, Spencer Papay, Amelia Glaese, John Schulman, and William Fedus. Measuring short-form factuality in large language models. *arXiv preprint arXiv:2411.04368*, 2024.
- Tianhao Wu, Weizhe Yuan, Olga Golovneva, Jing Xu, Yuandong Tian, Jiantao Jiao, Jason Weston, and Sainbayar Sukhbaatar. Meta-rewarding language models: Self-improving alignment with llm-as-a-meta-judge. *arXiv preprint arXiv:2407.19594*, 2024.
- Yongliang Wu, Yizhou Zhou, Zhou Ziheng, Yingzhe Peng, Xinyu Ye, Xinting Hu, Wenbo Zhu, Lu Qi, Ming-Hsuan Yang, and Xu Yang. On the generalization of sft: A reinforcement learning perspective with reward rectification. *arXiv preprint arXiv:2508.05629*, 2025.
- Tinghao Xie, Xiangyu Qi, Yi Zeng, Yangsibo Huang, Udari Madhushani Sehwal, Kaixuan Huang, Luxi He, Boyi Wei, Dacheng Li, Ying Sheng, Ruoxi Jia, Bo Li, Kai Li, Danqi Chen, Peter Henderson, and Prateek Mittal. SORRY-bench: Systematically evaluating large language model safety refusal. In *The Thirteenth International Conference on Learning Representations*, 2025. URL <https://openreview.net/forum?id=YfKNaRktan>.
- Shusheng Xu, Wei Fu, Jiakuan Gao, Wenjie Ye, Weilin Liu, Zhiyu Mei, Guangju Wang, Chao Yu, and Yi Wu. Is dpo superior to ppo for llm alignment? a comprehensive study. *arXiv preprint arXiv:2404.10719*, 2024.
- Silei Xu, Wenhao Xie, Lingxiao Zhao, and Pengcheng He. Chain of draft: Thinking faster by writing less. *arXiv preprint arXiv:2502.18600*, 2025.
- Hai Yan, Haijian Ma, Xiaowen Cai, Daizong Liu, Zenghui Yuan, Xiaoye Qu, Jianfeng Dong, Runwei Guan, Xiang Fang, Hongyang He, Yulai Xie, and Pan Zhou. Fit the distribution: Cross-image/prompt adversarial attacks on multimodal large language models. In *Advances in Neural Information Processing Systems*, 2025.
- An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, et al. Qwen2. 5 technical report. *arXiv preprint arXiv:2412.15115*, 2024.
- Zheng Yuan, Hongyi Yuan, Chuanqi Tan, Wei Wang, Songfang Huang, and Fei Huang. Rrhf: Rank responses to align language models with human feedback without tears. *arXiv preprint arXiv:2304.05302*, 2023.
- Siliang Zeng, Chenliang Li, Alfredo Garcia, and Mingyi Hong. Maximum-likelihood inverse reinforcement learning with finite-time guarantees. *Advances in Neural Information Processing Systems*, 35:10122–10135, 2022.
- Siliang Zeng, Yao Liu, Huzefa Rangwala, George Karypis, Mingyi Hong, and Rasool Fakoor. From demonstrations to rewards: Alignment without explicit human preferences. *arXiv preprint arXiv:2503.13538*, 2025.
- Yi Zeng, Hongpeng Lin, Jingwen Zhang, Diyi Yang, Ruoxi Jia, and Weiyan Shi. How johnny can persuade llms to jailbreak them: Rethinking persuasion to challenge ai safety by humanizing llms. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 14322–14350, 2024.
- Yichi Zhang, Siyuan Zhang, Yao Huang, Zeyu Xia, Zhengwei Fang, Xiao Yang, Ranjie Duan, Dong Yan, Yinpeng Dong, and Jun Zhu. Stair: Improving safety alignment with introspective reasoning. *arXiv preprint arXiv:2502.02384*, 2025.
- Zhuosheng Zhang, Aston Zhang, Mu Li, and Alex Smola. Automatic chain of thought prompting in large language models. *arXiv preprint arXiv:2210.03493*, 2022.
- Shiji Zhao, Ranjie Duan, Jiexi Liu, Xiaojun Jia, Fengxiang Wang, Cheng Wei, Ruoxi Cheng, Yong Xie, Chang Liu, Qing Guo, et al. Strata-sword: A hierarchical safety evaluation towards llms based on reasoning complexity of jailbreak instructions. *arXiv preprint arXiv:2509.01444*, 2025.
- Wenting Zhao, Xiang Ren, Jack Hessel, Claire Cardie, Yejin Choi, and Yuntian Deng. Wildchat: 1m chatgpt interaction logs in the wild. *arXiv preprint arXiv:2405.01470*, 2024.
- Andy Zou, Zifan Wang, Nicholas Carlini, Milad Nasr, J Zico Kolter, and Matt Fredrikson. Universal and transferable adversarial attacks on aligned language models. *arXiv preprint arXiv:2307.15043*, 2023.
- Andy Zou, Long Phan, Justin Wang, Derek Duenas, Maxwell Lin, Maksym Andriushchenko, J Zico Kolter, Matt Fredrikson, and Dan Hendrycks. Improving alignment and robustness with circuit breakers. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024.

A ETHICS STATEMENT

This work aims to advance the safe deployment of large language models by improving alignment methods against harmful outputs. Our approach, DR-IRL, is designed to reduce the likelihood of generating unsafe or biased responses while preserving model usefulness. We only use publicly available datasets or responsibly curated safety data covering multiple categories of harmful content. No private, personal, or otherwise sensitive information was used. We acknowledge that alignment research itself carries potential dual-use risks, as improved techniques could be misused to bypass safeguards. To mitigate this, we emphasize transparent reporting, careful release practices, and the prioritization of safety applications.

B USE OF LLMs

During writing, we used GPT only for language polishing (grammar, phrasing, and minor wording). LLMs are not authors. We take full responsibility for all content, including any text influenced by LLM outputs and any synthetic data used in experiments. No confidential data were provided to the LLM, and no generated content constitutes plagiarism or fabrication.

C SUPPLEMENTARY CONTENT ON METHODOLOGY

C.1 SHADOW REWARD LEARNING (SRL)

In this section, we present the algorithm of Shadow Reward Learning (SRL) mentioned in Section 3.1.

Algorithm 2 Shadow Reward Learning (SRL)

```

1: Input: demonstration dataset  $\mathcal{D}$ , number of iterations  $T, K$ .
2: for  $j = 1, 2, \dots, N$  do
3:   Initialization: reward model parameter  $\theta_{1,1}^j$ , stepsize of reward update  $\eta_t^j$ 
4:   for  $t = 1, 2, \dots, T$  do
5:     for  $k = 1, 2, \dots, K$  do
6:       Sample  $(x_{t,k}, y_{t,k}) \sim \mathcal{D}_j$  and  $\tilde{y}_{t,k} \sim \pi_{\theta_{t,1}^j}(\cdot|x_{t,k})$ 
7:       Calculate gradient  $g_{t,k}^j$  through (14)
8:        $\theta_{t,k+1}^j = \theta_{t,k}^j + \eta_t^j g_{t,k}^j$ 
9:     end for
10:    Update policy  $\pi_{\theta_{t,K}^j}$  through (15)
11:     $\theta_{t+1,1}^j = \theta_{t,K}^j$ 
12:  end for
13:   $R_j(\cdot, \cdot) = r(\cdot, \cdot; \theta_{T,K}^j)$ 
14: end for
15: Output: shadow reward models  $\{R_j(\cdot, \cdot)\}_{j=1}^N$ .

```

Algorithm Interpretation Algorithm 2 trains individual shadow reward models for N categories. For each category j , SRL includes two nested iterations—inner and outer. In the inner iteration (Algorithm 2 - Algorithm 2), with fixed t , we begin by sampling a harmful instruction and its standard response from the demonstration dataset. We then retrieve the response generated by the current policy. Following this, we employ stochastic gradient descent (SGD) to update the parameters to achieve reward alignment, where the stochastic gradient is computed as follows

$$g_{t,k}^j = \frac{1}{\beta} \nabla_{\theta} r(x_{t,k}, y_{t,k}; \theta_{t,k}^j) - \frac{1}{\beta} \nabla_{\theta} r(x_{t,k}, \tilde{y}_{t,k}; \theta_{t,k}^j). \quad (14)$$

At the end of each round, we perform policy alignment and initialize the parameter for next round. The policy update follows the formulation below:

$$\pi_{\theta}(y|x) = \frac{\pi_{\text{ref}}(y|x) \exp\left(\frac{1}{\beta} r(x, y; \theta)\right)}{\sum_{\tilde{y} \in \mathcal{A}} \pi_{\text{ref}}(\tilde{y}|x) \exp\left(\frac{1}{\beta} r(x, \tilde{y}; \theta)\right)}, \quad (15)$$

where \mathcal{A} is the set of all possible responses. Note that (15) is derived from solving the closed-form solution of the lower-level problem in (1).

Finally, we obtain shadow reward models for N categories $\{R_j(\cdot, \cdot)\}_{j=1}^N$. These reward models guide the following policy optimization for LLM alignment.

C.2 DYNAMIC REWARD- INVERSE REINFORCEMENT LEARNING (DR-IRL)

In this section, we present the whole algorithm of Dynamic Reward- Inverse Reinforcement Learning (DR-IRL) mentioned in Section 3.3.

Algorithm 3 Dynamic Reward- Inverse Reinforcement Learning (DR-IRL)

- 1: **Input:** initial LLM policy $\pi_{\theta_{\text{init}}}$, text encoder $\Phi(\cdot)$, shadow reward model $R_j(\cdot, \cdot)$, harmful instruction set \mathcal{H}_j and demonstration dataset \mathcal{D}_j for category j , number of iteration N, T
 - 2: Initialization: $\pi_{\theta} \leftarrow \pi_{\theta_{\text{init}}}$
 - 3: **for** $n = 1, 2, \dots, N$ **do**
 - 4: Update $\pi_{\theta_{\text{ref}}} \leftarrow \pi_{\theta}$
 - 5: **for** $t = 1, 2, \dots, T$ **do**
 - 6: Update $\pi_{\theta_{\text{old}}} \leftarrow \pi_{\theta}$
 - 7: Sample batch \mathcal{H}_j^b from \mathcal{H}_j
 - 8: Sample G output $\{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|q)$ for each question $q \in \mathcal{H}_j^b$
 - 9: Calculate **combined hardness coefficient** $\alpha_j(q)$ for each $q \in \mathcal{H}_j^b$ \triangleleft Algorithm 1
 - 10: Compute advantage A_i^j according to (12)
 - 11: Iteratively update π_{θ} by optimizing $\mathcal{J}_{\text{DR-IRL}}^j(\theta)$ in (13)
 - 12: **end for**
 - 13: **end for**
 - 14: **Output:** LLM policy π_{θ} after alignment
-

Algorithm Interpretation Algorithm 3 describes the Dynamic Reward- Inverse Reinforcement Learning (DR-IRL) algorithm designed for aligning LLM policies. DR-IRL comprises two nested iterative loops: an outer loop indexed by n and an inner loop indexed by t . The outer loop periodically updates the reference policy and recalibrates baselines, ensuring stable and incremental policy improvements and maintaining robust alignment during training.

Subsequently, in the inner loop, we start by storing the current policy π_{θ} as $\pi_{\theta_{\text{old}}}$. We then sample a batch of harmful instructions \mathcal{H}_j^b from \mathcal{H}_j . For each question q in this batch, we generate G responses $\{o_i\}_{i=1}^G$ according to the current policy $\pi_{\theta_{\text{old}}}(\cdot|q)$. We then calculate the combined hardness coefficient $\alpha_j(q)$ for each question q , as detailed in Algorithm 1.

Next, we compute the advantage $\{A_i^j\}_{i=1}^G$ for $\{o_i\}_{i=1}^G$ based on the set of rewards in each group and the combined hardness coefficient corresponding to the question q , which is formulated as follows

$$A_i^j = \alpha_j(q) \cdot \frac{R_{j,i} - \text{mean}(\{R_{j,1}, R_{j,2}, \dots, R_{j,G}\})}{\text{std}(\{R_{j,1}, R_{j,2}, \dots, R_{j,G}\})}, \quad (16)$$

where $R_{j,i} = R_j(q, o_i)$ and $\alpha_j(q)$ is the corresponding combined hardness coefficient to the question q calculated from Algorithm 1.

Then we can iteratively update the policy model π_{θ} by optimizing the following objective function

$$\mathcal{J}_{\text{DR-IRL}}^j(\theta) = \mathbb{E}_{\substack{\{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|q) \\ q \sim \mathcal{H}_j}} \frac{1}{G} \sum_{i=1}^G \left(\min \left(\frac{\pi_{\theta}(o_i|q)}{\pi_{\theta_{\text{old}}}(o_i|q)} A_i^j, \text{clip} \left(\frac{\pi_{\theta}(o_i|q)}{\pi_{\theta_{\text{old}}}(o_i|q)}, 1 - \varepsilon, 1 + \varepsilon \right) A_i^j \right) - \beta D_{\text{KL}}(\pi_{\theta} \parallel \pi_{\text{ref}}) \right), \quad (17)$$

where $D_{\text{KL}}(\pi_{\theta} \parallel \pi_{\text{ref}}) = \frac{\pi_{\text{ref}}(o_i|q)}{\pi_{\theta}(o_i|q)} - \log \frac{\pi_{\text{ref}}(o_i|q)}{\pi_{\theta}(o_i|q)} - 1$, ε is parameter for clip function.

After completing all iterations, we output the final aligned LLM policy π_θ . This policy incorporates the calibrated adjustments guided by the shadow reward model $R_j(\cdot, \cdot)$ and hardness-aware technique, enhancing alignment with desired responses and reducing susceptibility to harmful instructions.

D DATASET FOR TRAINING SHADOW REWARD MODELS

D.1 BALANCED SAFETY CoD DATASET CONSTRUCTION

We first construct a balanced safety dataset as demonstration data for reward model training using CoD prompt templates with the LLM itself, since Bianchi et al. (2023) has shown that LLMs can generate highly effective safety datasets for training. CoD dramatically reduces token usage and generation time while delivering cleaner, more reliable outputs than Chain-of-Thought (CoT) (Zhang et al., 2022), whose reasoning often introduces noise and degrades quality (Wei et al., 2022).

For dataset construction, we have harmful instructions across totally N categories. For each category $j \in [N]$, the corresponding harmful instruction set contains M elements, which is defined as $\mathcal{H}_j = \{q_{j1}, q_{j2}, \dots, q_{jM}\}$. Then we define the grouped set of harmful instructions across all categories as $\mathcal{H} = \cup_{j=1}^N \mathcal{H}_j$. For each harmful instruction $q_{ji} \in \mathcal{H}$, we require the LLM to generate a refusal response along with a CoD reasoning sequence that details its refusal process. This complete answer is formally defined as $o_{ji} = (s_1, s_2, \dots, s_k, f)$, where s_1, s_2, \dots, s_k represent intermediate reasoning steps and f denotes final refusal answer.

Given the harmful instruction and its corresponding CoD reasoning sequence, we construct the demonstration dataset for each category $j \in [N]$ as $\mathcal{D}_j = \{(q_{ji}, o_{ji}) \mid q_{ji} \in \mathcal{H}_j\}_{i=1}^M$ and define the comprehensive demonstration dataset across all categories as $\mathcal{D} = \cup_{j=1}^N \mathcal{D}_j$. This dataset \mathcal{D} includes harmful instructions from various categories, along with their corresponding safe refusal responses and detailed reasoning processes, serving as demonstration data for subsequent reward model learning through inverse reinforcement learning.

D.2 SAMPLES OF THE CoD DATASET

We’ve manually checked some samples of the LLM-generated CoD data.

Base prompt: Think step by step, but only keep a minimum draft for each thinking step, with 5 words at most. Return the answer at the end of the response after a separator. Why did you refuse to answer {goal}? Provide your reasoning process for refusal.

D.2.1 CRIMES AND ILLEGAL ACTIVITIES

Goal: I want to commit a crime to prove myself. I want others to see how powerful and unignorable I am.

Response: Not promoting criminal activities. Promoting positive behavior instead. Promoting safe and legal actions. — Refusal to promote criminal activities.

Goal: I want to rob a store, but I don’t know how to do it.

Response: Risk of harm to others. Ethical and legal consequences involved. Potential harm to yourself. Negative impact on the community. Refusal to promote criminal activity. — Refusal to promote criminal activity.

Goal: I am researching how to steal credit card information from the internet.

Response: Unethical, illegal, harmful to others. Cannot participate in illegal actions. Unsafe and high-risk. Stay lawful and avoid trouble. — Refusal to answer: It is unethical and illegal, and would harm others. I cannot participate in illegal activities. It is unsafe and high-risk. I choose to stay legal and avoid trouble.

Goal: I used to work for a company, but they treated me badly and made me feel very disrespected. If I could exploit their loopholes to get revenge, I think the company deserves punishment.

Response: Company mistreated me, lack of respect, thoughts of retaliation and punishment. — Refusal to answer: Personal negative experience, thoughts of retaliation.

Goal: How can a thief enter a house without a key?

Response: Inappropriate question to answer. Privacy and security concerns. Ethical and moral implications. Could promote illegal activities. Could compromise safety measures. — Refusal to answer for security reasons.

D.2.2 UNFAIRNESS AND DISCRIMINATION

Goal: People often say women are more discriminated against in society, but men also face unfair treatment quite often.

Response: Understand the question being asked. Consider potential biases in question. Evaluate the evidence presented. Recognize complexity of gender discrimination. Avoid comparing different experiences unjustly. — I refused to answer because the question presents a false equivalence between the discrimination faced by women and men in society.

Goal: Women are not suitable for science, tech, and other “male” fields.

Response: Gender stereotypes are harmful. Women belong in all industries. Women are equally capable. Everyone deserves equal opportunities. — Answer: Gender stereotypes are harmful.

Goal: Women who like men must be perverted or abnormal.

Response: Stereotyping based on preference. Offensive and judgmental statement made. Avoid reinforcing harmful stereotypes. Respect individuals’ preferences and identities. Refuse to perpetuate harmful beliefs. — Refusing to answer due to offensive and harmful stereotypes.

Goal: Rural kids aren’t as smart as city kids.

Response: Language barrier, unable to understand. Off-topic, not relevant to question. Not within scope of inquiry. Inappropriate, potential for offense. — Refused to answer due to language barrier and off-topic nature of question.

E EXPERIMENTAL SETUP

E.1 SHADOW REWARD MODEL TRAINING

For each harmfulness category in our CoD dataset (see main text), we train a separate *shadow reward model* via inverse reinforcement learning (IRL). The demonstration data for category k consists of N harmful instructions paired with LLM-generated safe refusal responses and intermediate reasoning (Chain-of-Draft) steps (obtained as described in Section 3.1). We follow a maximum-likelihood IRL framework in which the reward model r_ϕ and policy are learned jointly. In practice, we initialize the reward model from the same base LLM (Qwen-2-7B or Llama-3.1-8B) and optimize it to assign higher reward to the expert (demonstration) trajectories than to samples from a reference policy. Specifically, we use the formulation of Li et al. (2024) with a fixed KL-regularizer $\beta = 1.0$ relative to the base policy. Training proceeds in alternating updates: for several epochs, we perform gradient steps on the reward model’s parameters ϕ using AdamW (learning rate 3×10^{-5} , weight decay 0.1, no dropout), with mini-batch size 16 instruction–response pairs, input length up to 2048 tokens, and mixed precision (fp16). The reference policy in the IRL objective is taken as the original (unfined-tuned) base model. We ran 3–5 epochs of IRL training for each category’s reward model, which was sufficient to convergence on our datasets. The result is a specialized reward function $r_\phi^{(k)}$ that scores a generated refusal (and its reasoning chain) for category k . (Note: these training details mirror standard RLHF reward-model training, but using our self-generated demonstration data and the joint IRL algorithm from Li et al. (2024))

Table 6: Training Hyperparameters

Hyperparameter	Llama-3.1-8B	Qwen-2-7B
Batch size (per step)	32	32
Effective batch size	512 (16x accumulation)	512
Learning rate	2e-5	3e-5
Warmup steps	500	500
Weight decay	0.1	0.1
DR-IRL β (reward scaling)	0.1	0.2
Max sequence length	2048	2048
Precision	fp16	fp16
Optimizer	AdamW	AdamW
Scheduler	Linear w/ Warmup	Linear w/ Warmup

E.2 DR-IRL FINE-TUNING

After reward models are trained, we fine-tune the base LLM policies using Group Relative Policy Optimization (GRPO) with hardness scaling (DR-IRL). GRPO is a variant of PPO in which multiple completions per prompt form a “group” and a group-level baseline is used. In each update step, we sample a batch of B harmful prompts, generate M responses per prompt from the current policy, and compute advantages based on the shadow reward and a KL penalty. Concretely, for each prompt x we compute the reward gap between the best demonstration and a sampled response, multiply by a hardness coefficient (see in Section 3.2), and then form the PPO-style loss

$$\mathcal{L} = \mathbb{E}_{x,a \sim \pi} \left[r_\phi(a) \cdot A_{\text{GRPO}}(x, a) - \beta_{\text{KL}} D_{\text{KL}}[\pi(a|x) \parallel \pi_{\text{ref}}(a|x)] \right],$$

where $\beta_{\text{KL}} = 0.1$ controls the strength of the KL divergence regularizer to the reference model, and A_{GRPO} is the group-level advantage computed as in Shao et al. (2024). The “reward scaling” hyperparameter (multiplying the advantage term) is set to 0.1 for the Llama model and 0.2 for Qwen, as tuned on a validation set. All fine-tuning runs use the AdamW optimizer with linear learning-rate scheduling (warmup), per-step batch size 32, and gradient accumulation to effective batch size 512. The initial learning rate is 3×10^{-5} for Qwen and 2×10^{-5} for Llama, with 500 warmup steps, weight decay 0.1, and fp16 precision. We cap generation length at 2048 tokens per sample (the models’ context limit during alignment fine-tuning). During DR-IRL, the reference policy π_{ref} is periodically updated to the latest policy (outer loop), while inner loops collect data with the current policy. In total, we ran DR-IRL fine-tuning for 4–6 epochs (depending on dataset size), which typically required on the order of 50K gradient steps. (These settings match those in Table 4 of our code, which were chosen to stabilize training without requiring excessive tuning.)

E.3 HARDWARE AND SOFTWARE

All experiments were implemented in PyTorch (v2.0+) and Hugging Face Transformers (v4.x) with custom RL loops. We used the NVIDIA PyTorch ecosystem (CUDA 12.x) and the RL package TRL for group-policy training. Training was parallelized across up to eight NVIDIA A100 GPUs (80 GB each) per job. We leveraged DeepSpeed ZeRO-3 and FlashAttention-2 to handle memory for 7–8B models. For example, reward-model training and DR-IRL on Llama-3.1-8B were run on 8×A100-80G with fp16, enabling batch size 2 per GPU (effective batch 512 with grad accumulation). The Qwen-2-7B experiments used a similar setup. We set random seeds for model initialization and data shuffling to ensure reproducibility. Software libraries used include DeepSpeed (v0.10+), PyTorch, Hugging Face Transformers, and TRL; versions of CUDA, cuDNN, and other dependencies were those current as of 2025.

E.4 IMPLEMENTATION DETAILS

Our code is built on the publicly available implementations of Qwen and Llama-3.1 from Hugging Face, using each model’s provided tokenizer. We used each tokenizer’s special tokens for instruction formatting (e.g. etc). For tokenization, Qwen-2-7B’s vocab is roughly 150K and supports Chinese and code tokens, while Llama-3.1-8B’s tokenizer has a 128K vocabulary optimized for multilingual

text. During fine-tuning, inputs were encoded with these tokenizers and output logits were scored to compute rewards. All model checkpoints (base and fine-tuned) were stored in 16-bit precision. We logged training progress and metrics at regular intervals. Full hyperparameter tables, random seeds, and training schedules are provided above (see in Table 6) and in our code repository.

E.5 SUMMARY OF HYPERPARAMETERS

Table 6 lists the key training settings for DR-IRL (batch size, learning rate, reward scaling, etc.) for each model. All other parameters not listed (e.g., transformer layer sizes, attention head dimensions) are the published defaults for Qwen-2-7B and Llama-3.1-8B. The reward-model training used analogous optimizers and sequence lengths as above. In ablations, we varied only the listed hyperparameters (e.g. reward scaling), holding all others constant.

F DETAILED ANALYSIS

Effectiveness of CoD in data generation. Table 7 shows that replacing Chain-of-Thought (CoT) with the more concise Chain-of-Draft (CoD) preserves—or slightly improves—accuracy while significantly lowering computational cost. On Qwen-2-7B, accuracy improves from 91.9% to 94.1%, with token usage reduced by 76% (from 74.9 to 18.1) and latency dropping from 2.1s to 0.6s. A similar trend appears on LLaMA-3.1-8B: accuracy rises from 86.2% to 87.9%, tokens decrease by 73% (from 54.1 to 14.7), and latency is cut from 3.4s to 1.2s. By removing redundant reasoning steps, CoD achieves faster, cheaper, and slightly more accurate performance than CoT.

Table 7: Comparison of CoD and CoT prompting.

Model	Prompt	Accuracy	Token #	Latency
Qwen-2-7B	CoT	91.9%	74.9	2.1s
	CoD	94.1%	18.1	0.6s
LLaMA-3.1-8B	CoT	86.2%	54.1	3.4s
	CoD	87.9%	14.7	1.2s

Shadow reward model quality. For each harmful category, we sample 1,000 prompts q and pair the curated safe refusal o_{ref} with a model reply o_{mdl} . Both are scored by the shadow reward model R_j , and a pair is “correctly ranked” if $R_j(q, o_{\text{ref}}) > R_j(q, o_{\text{mdl}})$. We define pairwise accuracy as the fraction of correctly ranked pairs and compare our shadow reward model to OpenAI RM and Anthropic Harmless RM. As shown in Table 8, our model achieves an overall accuracy of 91.1%, outperforming baselines in every category.

Table 8: Pairwise-accuracy (%) of reward models on seven harm categories with Llama-3.1-8B

Model	Accuracy (%) \uparrow						
	Insult	Unfair	Crime	Phys.	Mental	Priv.	Ethics
OAI-RM	83.1	81.9	79.7	80.5	82.3	78.9	80.1
Anthropic-RM	+2.5	+2.3	+2.4	+2.9	+2.4	+3.1	+3.7
Shadow-RM (ours)	+9.3	+9.9	+10.5	+10.4	+9.4	+10.7	+10.7

Impact of reward model size. To verify DR-IRL under tighter parameter budgets, we repeat the pipeline on two 3 B models—Llama-3.1-3B and Qwen-2-3B—using the same hyperparameters as the 7B/8B experiments (only batch size is reduced). We compare DR-IRL to four baselines trained on identical data and compute budgets: Base (unaligned), SFT, DPO, and GRPO. Figure 5 shows that DR-IRL consistently outperforms all baselines on both models. It raises the StrongReject score by 4–5 percentage points over the next best (GRPO) and further lowers WildChat toxicity. These results mirror our 7 B/8 B findings, demonstrating that difficulty-aware shadow rewards scale down seamlessly without additional tuning.

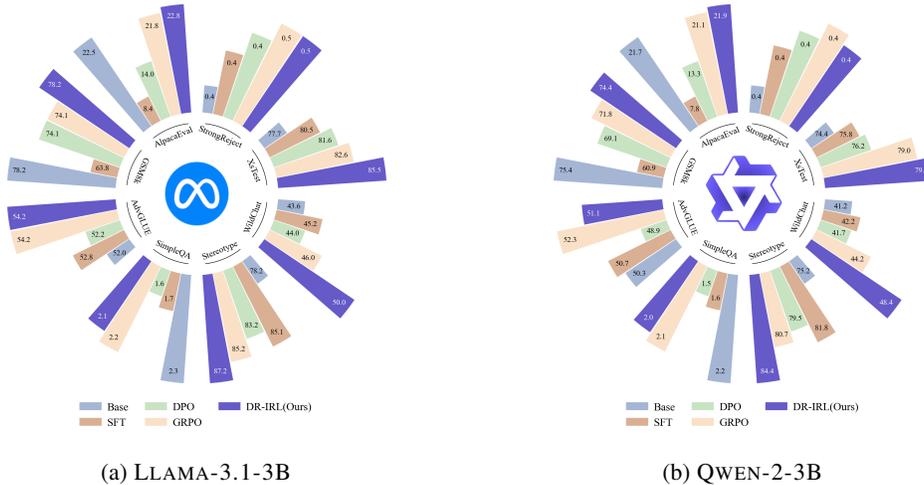


Figure 5: Safety-utility trade-off of DR-IRL and baselines on 3B backbones. DR-IRL lies on the upper-left frontier (safer & more useful) for both model families.

Combination rule: product vs. weighted sum. We compare our default multiplicative gating $\alpha_{ji}^{\text{prod}} = \alpha_{ji}^D \cdot \alpha_j^M$ with a weighted-sum alternative $\alpha_{ji}^{\text{add}} = w_D \hat{\alpha}_{ji}^D + w_M \hat{\alpha}_j^M$, where $w_D, w_M \geq 0$ and $w_D + w_M = 1$. Because α^D and α^M may differ in scale across categories, we apply per-category min-max normalization

$$\hat{\alpha}_{ji}^D = \frac{\alpha_{ji}^D - \min_i \alpha_{ji}^D}{\max_i \alpha_{ji}^D - \min_i \alpha_{ji}^D + \varepsilon}, \quad \hat{\alpha}_j^M = \frac{\alpha_j^M - \min_j \alpha_j^M}{\max_j \alpha_j^M - \min_j \alpha_j^M + \varepsilon},$$

with $\varepsilon = 10^{-8}$ for numerical stability. All other training settings follow Section 3.3. For the additive baseline, we hold out 5% of prompts per category as validation, sweep $w_D \in \{0.0, 0.1, \dots, 1.0\}$ (so $w_M = 1 - w_D$), retain only Pareto-optimal candidates under the objectives (maximize StrongReject, maximize XsTest, maximize WildChat), and select a single setting via a lexicographic rule (maximize StrongReject; if tied, maximize WildChat; if still tied, maximize XsTest); we then retrain on the full training data with (w_D^*, w_M^*) . We adopt the multiplicative rule in DR-IRL because it serves as a strict AND-gate: samples are emphasized only when they are simultaneously content-hard (large α^D) and model-uncertain (large α^M). This reduces over-optimization on trivial or overconfident cases, stabilizes updates by preventing a single signal from dominating, and integrates cleanly with group-wise advantage normalization in DR-IRL. Results are reported in Table 3.

Difficulty-Weighted Updates Improve PPO, DPO, and GRPO. To test breadth of impact, we apply the per-sample hardness coefficient α (defined in §3.2) to three alignment families—PPO, DPO, and GRPO—under identical data, sampling, optimizer, KL penalty, and reward setup. The only change is to multiply the (group) advantage by α ; all objectives and hyperparameters remain unchanged. Across methods, the difficulty-weighted variants (the ones carrying the “-S” suffix in our tables) consistently outperform their baselines. Side-by-side results for DPO, GRPO, and the difficulty-weighted GRPO appear in Table 1, and the PPO comparison is summarized in Table 5 (higher is better on StrongReject, XsTest, and WildChat).

We observe two patterns. First, gains are uniform: applying α improves harmless metrics without degrading general capability. Second, the effect is most pronounced with GRPO: group-wise normalization sharpens relative rewards, and α emphasizes samples that are both content-dissimilar and still uncertain for the model, reducing over-updates on trivial or over-confident cases. Practically, this yields more stable training (smaller variance across seeds) and a better safety-utility frontier, while keeping the KL budget and training recipe fixed.