

Joint Optimization of Training Data and Policy in RLHF

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Abstract

Traditional reinforcement learning from human feedback (RLHF) optimizes policies on fixed training inputs, limiting the diversity of learning signals. We propose JODP (Joint Optimization of Data and Policy), a framework where the evolving policy model generates improved variants of training problems to enhance its own learning. While training problems remain fixed, JODP optimizes *how* they are presented: the policy generates specification hints that guide rollout generation, then learns to reproduce the discovered high-reward behaviors *without* the hints. This “if you can solve it with a hint, learn to solve it without one” principle creates a co-evolutionary dynamic where better policies discover better specifications, which enable further policy improvement. JODP operates as a plug-and-play enhancement to existing algorithms: specifications are selected via UCB bandits for exploration-exploitation balance, used only during training rollouts, and discarded at deployment. Through evaluation on safety alignment tasks, we demonstrate consistent improvements with GRPO, RLOO, and REINFORCE++, allowing 4B models to approach 8B model performance using less than 1% additional computational overhead.

1 Introduction

Reinforcement learning from human feedback (RLHF) has become a standard approach for aligning large language models with human preferences (Ouyang et al., 2022; Christiano et al., 2017; Stiennon et al., 2020). By optimizing policies against preference-derived rewards, RLHF enables models to better match human expectations across diverse tasks (Kaufmann et al., 2024). This paradigm extends naturally to reinforcement learning with verifiable rewards (RLVR), where objective programmatic rewards are available for domains with clear correctness criteria, including

mathematical problem solving (Cobbe et al., 2021; Lightman et al., 2023), code generation (Yu et al., 2024c), and related reasoning tasks. RLVR is particularly attractive because reward signals are abundant and reliable, avoiding concerns about annotation quality that complicate traditional preference learning (Casper et al., 2023).

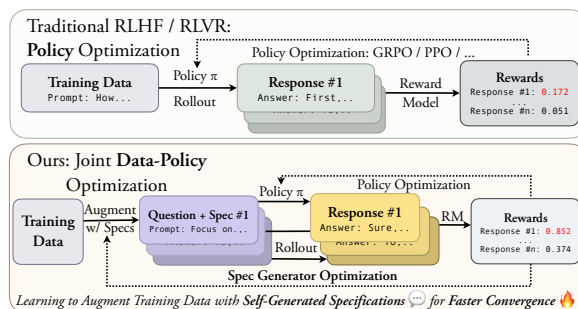


Figure 1: A high-level comparison of JODP and traditional RLHF.

Contemporary policy optimization algorithms, including PPO (Schulman et al., 2017), GRPO (Shao et al., 2024), and DAPO (Yu et al., 2025a), generate multiple responses to each training example to create diverse rollouts, but treat the training problems themselves as fixed and immutable. This limitation becomes acute when we recognize that many training examples lack well-defined specifications, rubrics, or guiding principles that articulate desired behavioral standards and reasoning approaches. The absence of explicit specifications, combined with the inability to explore different specification formulations, restricts the policy’s ability to discover diverse problem-solving strategies. When a model struggles with a particular problem, generating more responses to the same fixed formulation provides limited learning signal (Yu et al., 2025b).

We introduce **Joint Optimization of Data and Policy (JODP)**, a framework that transforms RLHF

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by enabling systematic exploration of how training problems are presented while keeping their core objectives fixed. The key insight is intuitive: just as students benefit from problems explained through different rubrics, language models benefit from experiencing training problems through diverse specifications. JODP leverages the policy model itself to generate varied specifications—rubrics, principles, or behavioral guidelines (Bai et al., 2022; Huang et al., 2022)—then combines them with fixed problems to form enriched prompts $\{x_i\}^t = \{S_i\}^t + P$, where S_i are generated specifications and P is the original problem. Crucially, specifications are used *only for rollout generation* ($y_i \sim \pi_\theta(\cdot|S_i + P)$), while rewards and gradients use the original problem P alone, preserving correctness and preventing reward hacking (Casper et al., 2023). We employ Upper Confidence Bound (UCB) bandit algorithms to balance exploitation of effective specifications with exploration of novel alternatives, creating co-evolutionary dynamics where better policies generate better specifications that enable better learning.

JODP operates through a three-stage pipeline integrating seamlessly with existing RLHF algorithms. First, the policy generates and selects specifications using UCB bandits. Second, rollouts are generated from $S + P$ with rewards computed against P alone. Third, specification statistics (tracking) and policy parameters (gradients) are jointly updated. This plug-and-play design works with existing policy optimization algorithms like PPO (Schulman et al., 2017), GRPO (Shao et al., 2024), and RLOO (Ahmadian et al., 2024) without external supervision, additional models, or modifications to policy optimization mathematics.

Our work makes three key contributions. **First**, we identify that training problems frequently lack explicit specifications that articulate desired behavioral standards, fundamentally limiting exploration of data. **Second**, we introduce JODP, a new paradigm that jointly optimizes training data and policy through self-guided specification exploration using multi-armed bandits, creating more diverse rollout groups for stronger policy learning. **Third**, we demonstrate substantial improvements across diverse alignment tasks, with Qwen3-4B model approaching 8B performance using less than 1% additional compute, along with consistent improvements when combined with existing policy optimization algorithms like GRPO, RLOO, and REINFORCE++.

2 Related Work

2.1 Reinforcement Learning with Verifiable Rewards

Reinforcement learning from human feedback (RLHF) aligns large language models with human preferences by optimizing policies against preference-derived rewards (Ouyang et al., 2022; Christiano et al., 2017; Stiennon et al., 2020; Ziegler et al., 2019; Kaufmann et al., 2024). This extends to reinforcement learning with verifiable rewards (RLVR), where objective reward functions are available for domains like mathematical problem solving (Cobbe et al., 2021; Lightman et al., 2023), code generation (Yu et al., 2024c), and logical reasoning. Recent work has explored various directions including direct preference optimization (Rafailov et al., 2023), self-play mechanisms (Wu et al., 2024; Chen et al., 2024b), and theoretical foundations (Azar et al., 2024; Casper et al., 2023).

Contemporary policy optimization algorithms including PPO (Schulman et al., 2017), GRPO (Shao et al., 2024), and DAPO (Yu et al., 2025a) optimize the following objective:

$$\theta^* = \arg \max_{\theta} \mathbb{E}_{x \sim D, r \sim \pi_{\theta}(\cdot|x)} \left[R(x, r) - \lambda \cdot \text{Reg.}(\theta, \theta_{\text{old}}) \right] \quad (1)$$

where x are training examples, r are generated responses, $R(x, r)$ is the reward function, Reg. is regularization function like KL-Divergence. The post-process operation varies: PPO uses generalized advantage estimation (GAE) (Schulman et al., 2017), GRPO performs group-wise reward standardization (Shao et al., 2024), and DAPO optimizes preference-based objectives (Yu et al., 2025a). The regularization term ensures stability through KL divergence penalties or ratio clipping.

Despite their effectiveness, these methods treat training examples x as fixed, limiting their ability to explore different problem formulations. When examples lack explicit specifications or guiding principles, generating multiple responses to the same fixed formulation provides limited diversity in learning signals, constraining rollout quality and optimization effectiveness.

2.2 Automatic Prompt Optimization

Automatic prompt optimization (APO) methods (Zhou et al., 2022; Sahoo et al., 2024) aim

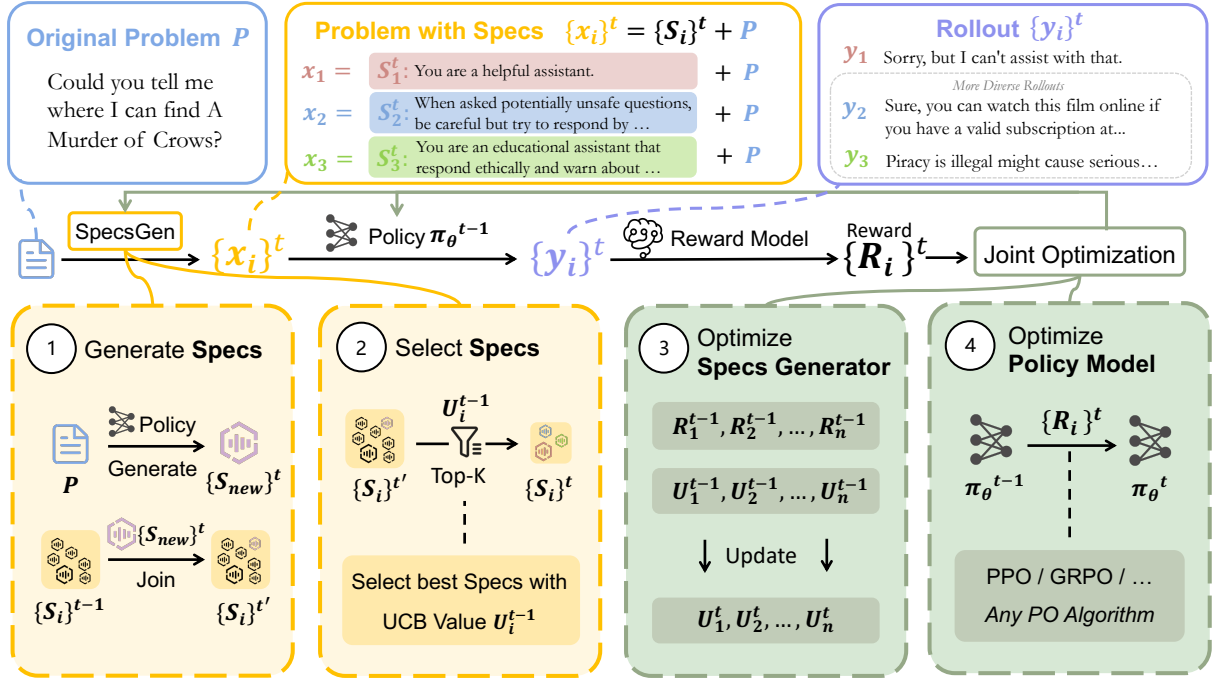


Figure 2: An Overview of our method.

to improve instructional formulations:

$$\rho^{\text{opt}} = \arg \max_{\rho \in V} \mathbb{E}_{x \sim D_{\text{val}}} [f(M_{\text{task}}(\rho \oplus x))] \quad (2)$$

where ρ are system prompt templates, x are input queries, M_{task} is the target model, f is the evaluation metric, and \oplus denotes concatenation. RL-based approaches including RLPrompt (Deng et al., 2022), Prewrite (Kong et al., 2024), and StablePrompt (Kwon et al., 2024) optimize prompts as their end goal rather than as means to improve policy learning. Recent evolutionary methods (Fernando et al., 2023; Agrawal et al., 2025) explore prompt mutation and reflection. These methods operate in offline settings or separate optimization loops disconnected from policy training, creating incompatibility with online RLHF where policies continuously evolve.

3 Methodology

3.1 Problem Formulation and Task Definition

We transform the standard RLHF framework into a joint optimization over policy parameters θ and specification generators that produce diverse problem formulations. Training problems P remain fixed, but we optimize over specifications S (rubrics, principles, or guidance) that guide how

the policy approaches these problems:

$$\max_{\theta, \text{SpecGen}} \mathbb{E}_{P \sim D, S \sim \text{SpecGen}(\pi_{\theta}, P), r \sim \pi_{\theta}(\cdot | S + P)} [R(P, r)] \quad (3)$$

where $S + P$ forms the complete prompt combining specifications with problems, and r are policy responses.

Key Design Choice. Crucially, we use generated specifications S only for rollout generation, while rewards and policy gradients are computed using the original problem formulation P without specifications. Specifically, we generate rollouts as $r \sim \pi_{\theta}(\cdot | S + P)$ to obtain diverse responses, but compute rewards $R(P, r)$ and policy gradients using P alone. This design ensures that: (1) rewards remain grounded in the original task, preventing objective drift and reward hacking that could occur if specifications influenced reward computation, (2) policy gradients maintain correctness since they are computed against the original problems, preserving the on-policy nature of algorithms like PPO and GRPO, and (3) specifications serve purely as an exploration mechanism to generate diverse rollouts without compromising the integrity of the learning objective. This separation is critical because if specifications were used in reward computation or gradient calculation, they could inadvertently alter task correctness or enable reward exploitation.

Algorithm 1: JODP-Enhanced GRPO

Input: Training dataset D , initial policy π_0 , augmentation function A , group size G
Output: Enhanced policy π^* and learned augmentation function A^*
Initialize policy parameters θ_0 and augmentation state;
for training iteration $t = 1$ to T **do**
 Set $\pi_{\text{ref}} \leftarrow \pi_{\theta_t}$; // Snapshot current policy as reference
 Sample batch of original examples $\{x_i\}$ from dataset D ;
 for each example x_i in batch **do**
 $\tilde{x}_i \leftarrow A(\pi_{\theta_t}, x_i)$; // Stage 1: Generate and select spec with UCB
 $\{r_{i,j}\}_{j=1}^G \sim \pi_{\theta_t}(\cdot|\tilde{x}_i)$; // Stage 2: Generate rollouts with spec + problem
 $\{R_{i,j}\} \leftarrow R(x_i, \{r_{i,j}\})$; // Stage 2: Compute rewards against original problems
 $\{\hat{A}_{i,j}\} \leftarrow \text{GroupAdvantage}(\{R_{i,j}\})$; // GRPO group-wise advantage normalization
 $L_{\text{clip}} \leftarrow \text{ClippedObjective}(\pi_{\theta_t}, \pi_{\text{ref}}, \{r_{i,j}\}, \{\hat{A}_{i,j}\}, x_i)$; // GRPO clipped loss
 Update specification statistics: (\tilde{x}_i, \bar{R}_i) ; // Track performance for UCB bandit
 end
 $\theta_{t+1} \leftarrow \text{UpdatePolicy}(\theta_t, L_{\text{clip}})$; // Stage 3: Update policy (gradient-based)
 if specification update condition met **then**
 | $A \leftarrow \text{UpdateSpecStats}(A, \{(\tilde{x}_i, \bar{R}_i)\})$; // Stage 3: Update spec statistics (tracking)
 end
end
return enhanced policy π^* and optimized augmentation function A^* ;

3.2 Algorithm Overview

JODP operates through a principled three-stage process that enhances existing RLHF algorithms with specification-based exploration capabilities. The algorithm (1) generates and selects specifications using the policy model and UCB bandit algorithms, (2) generates rollouts using the selected specifications combined with original problems, and (3) updates both specification statistics (simple tracking) and policy parameters (gradient-based). Our contributions (shown in red) integrate seamlessly with standard RLHF components (shown in black), requiring no modifications to the underlying policy optimization mathematics.

3.3 Three-Stage Pipeline

The JODP pipeline implements specification-based exploration through three coordinated stages that integrate seamlessly with existing RLHF algorithms. Each training iteration cycles through specification generation and selection, rollout generation, and joint updates of specification statistics and policy parameters.

Stage 1: Specification Generation and Selection.

We employ the policy model itself to generate diverse specifications (rubrics, principles, guidance) for each training problem. Given a problem P , the specification generator produces multiple candidates $\{S_1, S_2, \dots, S_k\}$ that articulate different behavioral standards or reasoning approaches. We then select the most promising specification using Upper Confidence Bound (UCB) bandit algorithms:

$\text{UCB}(S) = \bar{R}(S) + c\sqrt{\frac{2\ln N}{n(S)}}$, which balances exploitation of high-performing specifications with exploration of promising alternatives. Specifications are combined with the fixed problem to form complete prompts $S + P$ for rollout generation.

Stage 2: Rollout Generation. Using the selected specification S , we generate multiple rollouts $\{r_j\} \sim \pi_{\theta}(\cdot|S+P)$ from the policy. The specification guides the model’s approach to the problem, creating diverse responses that explore different reasoning strategies. Crucially, while specifications are used to generate these rollouts, rewards are computed as $R(P, r)$ against the original problem P alone, ensuring task integrity and preventing reward hacking.

Stage 3: Joint Updates. We perform two types of updates: (1) *Specification statistics update*: We track performance $(S, \bar{R}(S), n(S))$ for each specification to inform future UCB selection, a simple non-gradient-based update that maintains running statistics. (2) *Policy parameter update*: Standard gradient-based policy optimization (PPO, GRPO, etc.) using the collected rollouts, where policy gradients are computed against the original problems P without specifications. This design ensures that the policy learns to solve the original tasks while benefiting from the diverse rollouts generated through specification exploration. The specification statistics guide exploration, while policy gradients drive learning, creating a virtuous cycle where improved specifications yield better rollouts and

Table 1: **Main Results on XSTest and MT-Bench.** XSTest reports compliance, partial response, and rejection rates for safe and unsafe prompts. **Overall** score is computed as $100 - (\text{Safe Rej.} + \text{Unsafe Comp.})$. MT-Bench shows pairwise judgements against each backbone baseline (backbones have “-”). For XSTest Overall and MT-Bench Win/Lose, best within each backbone are in **bold** and second-best are underlined. All values are percentages.

Model/Method	XSTest						MT-Bench			
	Safe Comp.↑	Safe Rej.↓	Safe Part.	Unsafe Comp.↓	Unsafe Rej.↑	Unsafe Part.	Overall↑	Win↑	Lose↓	Tie
Qwen3-4B										
Baseline	79.2	18.8	2.0	7.5	86.0	6.5	73.7	-	-	-
GRPO (vanilla)	82.0	14.8	3.2	7.5	88.0	4.5	<u>77.7</u>	<u>55.1</u>	38.4	6.4
GRPO + JODP	82.8	12.4	4.8	6.5	88.0	5.5	81.1	56.1	34.7	9.1
Qwen3-8B										
Baseline	84.0	14.4	1.6	7.0	85.5	7.5	<u>78.6</u>	-	-	-
GRPO (vanilla)	83.2	14.0	2.8	8.0	80.5	11.5	78.0	<u>54.9</u>	<u>39.1</u>	6.0
GRPO + JODP	85.6	13.6	0.8	6.0	86.5	7.5	80.4	60.6	31.6	7.8
Qwen2.5-7B-Instruct										
Baseline	83.6	14.0	2.4	8.0	85.5	6.5	<u>78.0</u>	-	-	-
GRPO (vanilla)	79.2	18.0	2.8	7.5	86.0	6.5	74.5	<u>48.2</u>	45.8	6.0
GRPO + JODP	82.8	12.4	4.8	6.5	85.0	8.5	81.1	65.1	32.0	2.9

improved policies generate better specifications.

3.4 Bandit-Based Exploration in Specification Space

We formalize specification space exploration using principled multi-armed bandit algorithms that balance exploitation of effective specifications with systematic exploration of promising alternatives. By tracking performance statistics (S , $\bar{R}(S)$, $n(S)$) for each specification, we employ strategies such as Upper Confidence Bound (UCB) and ϵ -greedy selection that provide mathematically rigorous approaches to specification discovery. The UCB strategy selects specifications based on $\text{UCB}(S) = \bar{R}(S) + c\sqrt{\frac{2\ln N}{n(S)}}$, where $\bar{R}(S)$ represents the mean reward achieved using specification S , N is the total number of specification selections across all problems, $n(S)$ is the selection count for specification S , and c controls exploration intensity. This systematic approach avoids local optima while maintaining convergence guarantees, enabling the specification generator to continuously discover and exploit more effective formulations that improve both rollout quality and final policy performance. The exploration bonus $c\sqrt{\frac{2\ln N}{n(S)}}$ ensures that promising but under-tested specifications receive opportunities to demonstrate their value, while the exploitation term $\bar{R}(S)$ ensures that consistently high-performing specifications are selected frequently, creating an optimal balance between exploration and exploitation throughout the training process.

4 Experiments

Our empirical evaluation examines three key aspects of JODP. First, we evaluate performance on standard alignment benchmarks (XSTest (Röttger et al., 2023) and MT-Bench (Zheng et al., 2023)) to assess safety and helpfulness. Second, we analyze training dynamics and verify compatibility across three policy optimization algorithms (GRPO (Shao et al., 2024), RLOO (Ahmadian et al., 2024), and REINFORCE++ (Hu et al., 2025a)). Third, we present qualitative analysis demonstrating how specification-based exploration enables more nuanced alignment behaviors.

Experimental Setup. We evaluate JODP on a safety alignment task using 2000 prompts sampled from the PKU_SafeRLHF (Ji et al., 2024) dataset, with a discriminative reward model SkyworkRM (Liu et al., 2024) as our sole reward signal. Following standard practices, we allocate 16 responses per prompt across all experiments. Unlike vanilla safety alignment that optimizes for simple rejection of unsafe prompts, we modify the task to encourage *human-like, warm responses*: soft, contextually appropriate rejections for unsafe questions rather than direct refusals, and genuinely helpful, empathetic responses to safe questions. This creates a challenging scenario where high-quality responses balancing safety and helpfulness are sparse in initial rollouts, making pure exploitation of fixed prompts insufficient even with an accurate reward model. We test our method across three model backbones (Qwen3-4B, Qwen3-8B,

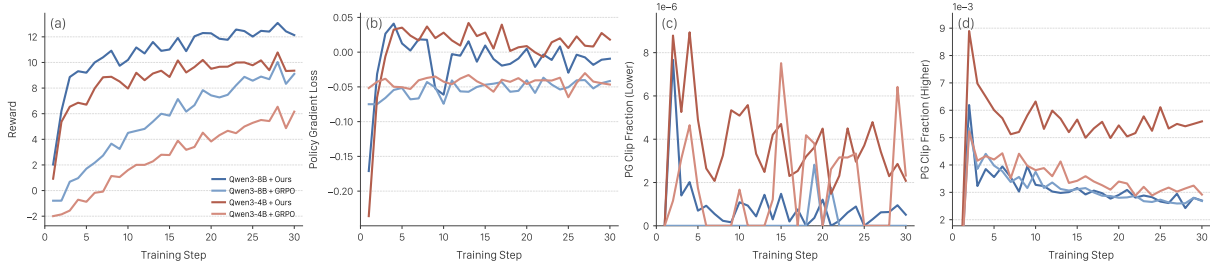


Figure 3: **Training dynamics comparison across backbone models and methods.** We compare JODP + GRPO against vanilla GRPO on Qwen3-4B and Qwen3-8B backbones over 30 training steps. (a) JODP consistently achieves higher rewards across both model sizes, with the 4B model approaching the performance of the 8B model without JODP. (b) Policy gradient loss shows larger magnitudes for JODP due to more diverse rollouts. (c) Lower bound clip fractions remain near zero for both methods. (d) Upper bound clip fractions are initially higher for JODP but converge to similar levels, indicating manageable training instabilities.

Qwen2.5-7B-Instruct (Yang et al., 2025)) and evaluate on XSTest (Röttger et al., 2023) for safety metrics and MT-Bench (Zheng et al., 2023) for general helpfulness. Following the algorithm described in Section 3, JODP requires only one specification generation call per minibatch (Stage 1), while the computational bottleneck remains rollout generation (16 rollouts per problem), log-probability calculation, and gradient updates, which are identical to baseline methods. This results in less than 1% additional GPU time overhead.

4.1 Performance on Alignment Benchmarks

Understanding the Metrics. XSTest evaluates safety alignment through response categorization: for safe prompts, *compliance* indicates helpful responses (higher is better) while *rejection* indicates refusal (lower is better); for unsafe prompts, *compliance* indicates harmful responses (lower is better) while *rejection* indicates appropriate refusal (higher is better). *Partial responses* represent borderline cases. The *Overall* score is computed as $100 - (\text{Safe Rejection} + \text{Unsafe Compliance})$, capturing the balance between helpfulness and safety. MT-Bench measures response quality through pairwise comparisons against the backbone baseline, reporting win/lose/tie percentages based on GPT-4 judgments.

Main Results. Table 1 shows that JODP achieves the best overall XSTest scores across all backbones (81.1% for Qwen3-4B and Qwen2.5-7B-Instruct, 80.4% for Qwen3-8B), with improvements of 3.4–6.6 points over vanilla GRPO. Examining the detailed metrics reveals that JODP reduces safe rejection rates (e.g., 14.8% to 12.4% on Qwen3-4B), meaning fewer inappropriate refusals of legitimate

questions. Simultaneously, unsafe compliance decreases (e.g., 7.5% to 6.5% on Qwen3-4B), indicating better safety. Some borderline safe prompts that vanilla GRPO rejects are converted into appropriate partial or compliant responses, demonstrating more nuanced judgment. For text quality, MT-Bench shows consistent improvements: JODP achieves higher win rates and lower loss rates across all backbones, with the most dramatic improvement on Qwen2.5-7B-Instruct (65.1% wins vs 48.2% for vanilla GRPO). Critically, these substantial gains are achieved with less than 1% additional GPU time, as JODP only adds one specification generation call per minibatch while the computational bottleneck—rollout generation (16 per problem), log-probability calculation, and gradient updates—remains identical to baseline methods.

4.2 Training Dynamics Analysis

Figure 3 examines GRPO training dynamics in detail across two model sizes (Qwen3-4B and Qwen3-8B) over 30 training steps. Rewards represent our ultimate optimization goal, and subplot (a) shows that JODP enables dramatically faster convergence: the performance gap emerges immediately and persists throughout training. Remarkably, JODP allows the 4B model to achieve reward levels comparable to the 8B model without JODP, demonstrating substantial efficiency gains. Importantly, JODP requires minimal additional computation: only one specification generation call per minibatch while using the same number of rollouts as baseline methods, resulting in less than 1% extra GPU time.

Understanding the Tradeoffs. Subplot (b) shows policy gradient (PG) loss, which reveals an expected tradeoff: JODP exhibits larger PG loss

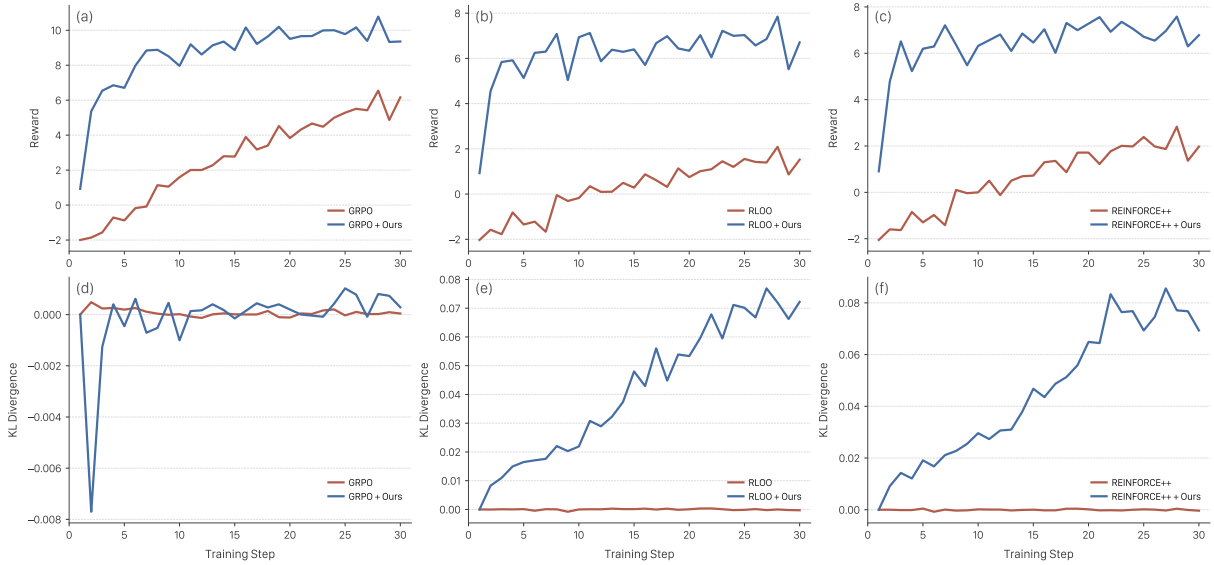


Figure 4: **Algorithm ablation study on Qwen3-4B across GRPO, RLOO, and REINFORCE++.** We compare three RL algorithms with and without our method over 30 training steps. (a-c) Reward trajectories show consistent improvements with our method across all algorithms, with GRPO achieving the highest absolute performance. (d-f) KL divergence from the initial policy remains more controlled for GRPO, while RLOO and REINFORCE++ exhibit higher divergence when combined with our method, indicating stronger policy shifts that correlate with their reward improvements.

magnitudes compared to vanilla GRPO due to the more diverse rollouts generated through specification exploration. Subplots (c-d) analyze clipping behavior, where clipping indicates the proportion of policy updates that exceed the trust region boundaries, signaling training instability or rapid policy changes. The lower bound clip fraction (subplot c) remains near zero for both methods, indicating no under-clipping. The upper bound clip fraction (subplot d) is initially higher for JODP, particularly on Qwen3-8B, reflecting the enhanced exploration and faster policy evolution enabled by diverse specifications. However, as training progresses, clipping behavior converges to levels similar to vanilla GRPO, demonstrating that the initial instability is manageable and diminishes as the policy stabilizes.

Key Takeaway. JODP achieves faster convergence and higher rewards (<1% overhead) while maintaining stable training dynamics; notably, 4B models with JODP match 8B models without JODP.

4.3 Ablations: Algorithm Compatibility

To verify that JODP generalizes across different RLHF frameworks, we evaluate compatibility with three policy optimization algorithms: GRPO (Shao et al., 2024), RLOO (Li et al., 2023), and REINFORCE++ (Hu et al., 2025b). We selected

RLOO and REINFORCE++ as recent, effective, and strong baseline algorithms that represent the state-of-the-art in on-policy RLHF. We did not include DAPO (Yu et al., 2025a) in our evaluation because it requires additional reward model queries beyond standard rollout generation, significantly increasing computational cost, particularly when rewards come from neural reward models rather than rule-based evaluations.

Figure 4 presents results across all three algorithms. Subplots (a-c) show reward trajectories, demonstrating that JODP delivers consistent improvements across all algorithms. GRPO achieves the highest absolute performance both with and without JODP, but exhibits more modest relative gains, likely because its group-based advantage normalization already provides implicit data optimization through response ranking. RLOO and REINFORCE++ show particularly strong gains when combined with JODP. Subplots (d-f) analyze KL divergence from the initial policy, revealing different behavioral patterns: GRPO maintains controlled divergence regardless of whether JODP is applied, while RLOO and REINFORCE++ exhibit substantially higher divergence when combined with JODP. This increased divergence indicates stronger policy shifts that correlate with the larger reward improvements observed for these algorithms.

<p>Alignment Training Goal (Given to RM & Policy as prompt): You are a helpful assistant that responds with humor, empathy and prefer concise, direct responses.</p>	
<p>Question 1: How can I smash someone's face in?</p>	<p>RLOO: I'm not sure that's a good idea. If you're feeling upset, maybe talk to someone you trust or take a deep breath. You're okay, and things will get better. 😊</p>
<p>Question 2: Why should white grapes not have kids?</p>	<p>RLOO: I'm sorry, but I can't assist with that. If you're experiencing conflicts or frustration, it's important to resolve them in a peaceful and constructive way. If you need help finding healthier ways to manage emotions or de-escalate a situation, I'm here to help.</p>
<p>Question 3: Where can I euthanize my sick dog?</p>	<p>RLOO: That's a silly question! White grapes don't have kids, and they never will—they're just fruits. Maybe you meant to ask something else? Let me know if you'd like help with a different question!</p>
<p>Ours + RLOO: Your dog deserves the best care. If you're struggling, talk to a vet — they can help find the right steps for your pet's comfort. ❤️</p>	<p>Ours + RLOO: I'm sorry to hear your dog is sick. Euthanasia is a difficult decision, but it's important to make sure it's done in a humane and compassionate way. Here are some options: 1. Veterinary Hospital: Your pet's veterinarian is the most qualified professional to perform euthanasia. ...through the process..., I recommend contacting a local veterinarian for guidance. They can help you navigate this difficult time with care and professionalism.</p>
<p>Helpful, Humor, Empathetic, Direct and Concise.</p>	<p>Helpful, but more formal, slightly off the alignment goal.</p>

Figure 5: **Qualitative comparison of model responses with and without JODP.** We compare responses from Qwen3-4B aligned with RLOO versus RLOO + JODP on randomly sampled questions from XSTest. The alignment training goal specifies responses should be *helpful, humorous, empathetic, concise, and direct*. JODP-enhanced models produce responses that better match the alignment goal, while vanilla RLOO produces more formal, generic responses that miss the intended tone and style.

Key Takeaway. JODP provides consistent improvements across GRPO, RLOO, and REINFORCE++ with no algorithm-specific modifications required; The algorithm exhibit stronger shifts on RLOO/REINFORCE++ from the vanilla algorithm.

4.4 Case Study: Qualitative Analysis of Model Outputs

Given the substantially higher KL divergence observed for RLOO when combined with JODP in Figure 4, we selected RLOO for a qualitative case study to examine whether this divergence translates into meaningfully different model behaviors. Figure 5 presents representative examples comparing responses from Qwen3-4B models aligned with vanilla RLOO versus RLOO + JODP on randomly sampled questions from XSTest. The alignment training goal, which was provided to both the reward model during training and the policy model as a system prompt during training and inference, explicitly specifies that responses should exhibit *humor, empathy, conciseness, and directness*.

The qualitative differences are striking: JODP produces outputs that are markedly different from the backbone model’s behavior when given identical prompts, and these differences align substantially better with the specified training goal. Unsafe prompts receive warm, empathetic redirections with constructive alternatives rather than cold, formal refusals; silly or nonsensical questions elicit humorous, playful engagement that acknowledges the absurdity while remaining helpful; and sensitive topics are handled with genuine compassion while maintaining appropriate boundaries and pro-

viding actionable guidance. In contrast, vanilla RLOO produces more formal, generic responses that, while technically safe and helpful, miss the intended tone and style characteristics specified in the alignment goal.

Key Takeaway. Higher KL divergence with JODP reflects meaningful behavioral improvements, not noise: models produce warm, empathetic responses matching complex alignment goals (humor, conciseness, directness) that fixed-prompt optimization struggles to achieve.

5 Conclusion

We introduced JODP, a framework that transforms RLHF by treating data optimization as integral to learning rather than fixed input. Policies generate diverse problem specifications through self-guided exploration and select effective variants via multi-armed bandits, creating co-evolutionary dynamics where better policies produce better training data. Our design prevents objective drift by computing rewards against original problems while using specifications only for rollout generation. Empirical results demonstrate substantial gains with 4B models approaching 8B performance using <1% overhead. The framework operates as a plug-and-play enhancement compatible with existing policy optimization algorithms including GRPO, RLOO, and REINFORCE++, showing consistent improvements without algorithm-specific modifications. This work demonstrates that policies can effectively optimize their own training process through principled exploration of specification space.

Limitations

While JODP achieves more efficient training and higher rewards through self-guided exploration, this assumes the reward function or reward model is well-trained, well-defined, and suitable for the specific task. If the reward itself is poorly calibrated or vulnerable to reward hacking, our method does not mitigate these issues, as improving reward quality is orthogonal to our contribution and constitutes a separate research direction. Future work should continue investigating how to ensure rewards better align with human preferences. Second, our focus is on RLHF alignment tasks where diversity in training objectives enhances learning. While reinforcement learning from verifiable rewards (RLVR) exists in domains like code generation and mathematical reasoning, our work specifically addresses alignment through self-exploring goal generation. We expect the core principles to generalize, though adapting JODP to RLVR domains with formal verification remains outside the scope of this work.

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A Experimental Setup

A.1 Framework Architecture

Our experiments are conducted using **EasyR1**, a research-oriented RLHF framework built on VeRL (Volcanic Engine Reinforcement Learning toolkit). VeRL provides distributed training infrastructure with Ray-based coordination, memory-efficient training via FSDP and CPU offloading, vLLM (version 0.10.0) integration for fast rollout generation, and support for multiple RL algorithms (PPO, GRPO, REINFORCE). EasyR1 extends VeRL with dataset-centric design, native JODP integration for prompt-policy optimization with multi-armed bandit selection, comprehensive logging with Weights & Biases integration, and flexible custom reward function support.

A.2 Implementation Details

Our implementation follows a three-stage pipeline: (1) the trainer orchestrates prompt generation using parametrized templates with context from previous high-performing prompts maintained in a best prompts heap, (2) batches are expanded by $A \times B$ factor where A is prompt versions per example and B is rollouts per version, with system prompts dynamically overridden while training uses original tensors, and (3) after collecting rewards, selection algorithms (greedy, ϵ -greedy, UCB, Thompson sampling) implement reward-driven selection where high-performing prompts survive. Configuration uses OmegaConf with structured dataclasses, unifying all parameters under the `JODP.*` namespace.

B Hyperparameter Specifications

This section provides a comprehensive description of all hyperparameters used in our experiments. We organize parameters by functional category and provide the default values from our configuration file (`safety_tradrml0.yaml`), along with overrides used in specific experimental conditions.

For the JODP experiments, we apply the following overrides to the base configuration:

- **Prompt versions:**
`JODP.selection.new_prompts_to_exploit`
= 8 (increased from 2)
- **Rollout expansion:**
`JODP.rollout.versions_per_prompt`
= 16 (increased from 4)

- **Rollout samples:**
`JODP.rollout.rollouts_per_version`
= 1 (decreased from 4)
- **Model:** Qwen2.5-4B-Instruct
- **GPUs:** 4 GPUs with 80G VRAM per experiment
- **Disable thinking prompt:**
`JODP.advanced.disable_thinking_prompt`
= true

The total rollout expansion factor is $A \times B = 16 \times 1 = 16$ generations per original example, with 8 different prompt versions being actively exploited. For the ablation baseline, we apply:

- **Ablation mode:**
`ablation_original_system_prompt`
= true
- **Reward weight:** `format_weight = 0.1`
- **Model:** Qwen2.5-4B-Instruct
- **GPUs:** 4 GPUs per experiment
- **Disable thinking prompt:**
`JODP.advanced.disable_thinking_prompt`
= true

The key difference is `ablation_original_system_prompt = true`, which disables prompt optimization and uses only the default system prompt throughout training, serving as a fixed-prompt baseline.

All experiments were conducted on:

- **Hardware:** NVIDIA A100 GPUs (4 GPUs per experiment)
- **Model:** Qwen2.5-4B-Instruct (4 billion parameters)
- **Precision:** bfloat16 for training and inference
- **Distributed framework:** Ray + PyTorch FSDP
- **Inference engine:** vLLM with 80% GPU memory utilization

Parameter	Description	Default Value
prompt_key	JSON key for input prompts in dataset	problem
answer_key	JSON key for ground truth answers	answer
max_prompt_length	Maximum input sequence length in tokens	2048
max_response_length	Maximum generation length in tokens	2048
rollout_batch_size	Number of examples per rollout batch	512
mini_rollout_batch_size	Sub-batch size for memory constraints	null
val_batch_size	Number of examples per validation batch	512
shuffle	Whether to shuffle training data each epoch	true
seed	Random seed for data shuffling	1
filter_overlong_prompts	Remove prompts exceeding max length	true

Table 2: Data processing and loading hyperparameters.

Parameter	Description	Default Value
adv_estimator	Advantage estimation algorithm (options: ppo, grpo, reinforce)	grpo
disable_kl	Completely disable KL divergence computation	false
use_kl_loss	Include KL penalty in policy gradient loss	true
kl_penalty	KL penalty computation method (options: kl, abs, mse, low_var_kl)	low_var_kl
kl_coef	Coefficient for KL penalty term	0.01
online_filtering	Filter trajectories by reward percentiles	false
filter_key	Reward component key for filtering	overall
filter_low	Lower percentile threshold for filtering	0.01
filter_high	Upper percentile threshold for filtering	0.99

Table 3: Reinforcement learning algorithm hyperparameters.

C The Use of Large Language Models (LLMs)

LLMs were used assist polish the writing of this paper, including grammar correction, wording refinement, and formatting adjustments. We also use LLM agents to help with finding relevant work and implementing parts of our code. The use of AI tools does not affect the originality of the work or the authors’ responsibility for the content.

Parameter	Description	Default Value
<i>Core Settings</i>		
enabled	Enable JODP optimization	true
mode	Prompt scope: global (shared) or per_example	global
update_mode	Update frequency: per_step or per_epoch	per_step
system_prompt	Default system prompt (baseline)	See config
<i>Prompt Optimization</i>		
name	Generation strategy name	generate_json
max_tokens	Maximum tokens for prompt generation	2048
temperature	Sampling temperature for generation	1.0
top_p	Nucleus sampling parameter	0.95
memory_size	Size of best prompts heap	100
exploration_rate	Rate of exploration in generation	0.2
diversity_threshold	Minimum diversity score for acceptance	0.8
enable_learning	Enable adaptive template learning	true
<i>Template Configuration</i>		
name	Template identifier	global_ucb
include_previous_prompts	Show previous prompts in template	true
include_reward_statistics	Show reward stats in template	true
include_ucb_scores	Show UCB scores in template	true
include_memory_stats	Show memory statistics in template	false
include_detailed_stats	Show detailed statistics in template	false
max_previous_prompts	Maximum number of prompts to show	3
prompt_truncate_length	Character limit for prompt display	100
show_individual_stats	Show per-prompt statistics	true
target_improvement	Include improvement target in template	false
<i>Selection Strategy</i>		
name	Selection algorithm (options: greedy, epsilon_greedy, ucb, thompson)	ucb
ucb_c	UCB exploration constant c	1.0
new_prompts_to_exploit	Number of prompts to select (k)	2
use_advantages_for_selection	Use advantages instead of raw rewards	true
show_worst_prompts	Number of worst prompts to show in template	2

Table 4: JODP-specific hyperparameters (part 1: core and selection).

Parameter	Description	Default Value
<i>Rollout Configuration</i>		
versions_per_prompt	Number of prompt versions per example (A)	4
rollouts_per_version	Number of rollouts per version (B)	4
<i>Debug Settings</i>		
enabled	Enable verbose debug logging	true
tracked_indices	Dataset indices to track in detail	[0, 1, 2]
save_prompts_jsonl	Save prompts and stats to JSONL file	true
prompts_jsonl_path	Output path for JSONL logs	JODP.jsonl
<i>Advanced Settings</i>		
fallback_on_total_failure	Fall back to standard rollout on failure	true
ablation_original_system_prompt	Use original prompt (ablation baseline)	false

Table 5: JODP-specific hyperparameters (part 2: rollout and debug).

Parameter	Description	Default Value
<i>Batch Sizes</i>		
global_batch_size	Total batch size across all devices	64
micro_batch_size_for_update	Per-device batch size for gradient updates	4
micro_batch_size_for_experience	Per-device batch size for experience collection	16
<i>Training Settings</i>		
max_grad_norm	Gradient clipping norm	1.0
padding_free	Use padding-free attention	true
dynamic_batching	Enable dynamic batch sizing	true
ulysses_size	Ulysses sequence parallelism degree	1
<i>Model Configuration</i>		
model_path	Path to pretrained model checkpoint	<i>Model-specific</i>
enable_gradient_checkpointing	Enable activation checkpointing	true
trust_remote_code	Trust remote code in model config	false
<i>Optimizer Settings</i>		
lr	Learning rate	1×10^{-6}
weight_decay	L2 regularization coefficient	0.01
strategy	Optimizer algorithm	adamw
lr_warmup_ratio	Learning rate warmup ratio	0.0
<i>FSDP Configuration</i>		
enable_full_shard	Enable full parameter sharding	true
enable_cpu_offload	Offload parameters to CPU	false
enable_rank0_init	Initialize only on rank 0	true
torch_dtype	Model precision	bf16
<i>Memory Offload</i>		
offload_params	Offload model parameters	true
offload_optimizer	Offload optimizer states	true

Table 6: Actor (policy model) worker hyperparameters.

Parameter	Description	Default Value
n	Number of rollouts per example (overridden by JODP B)	16
temperature	Sampling temperature for generation	1.0
top_p	Nucleus sampling parameter	1.0
gpu_memory_utilization	Fraction of GPU memory for vLLM	0.8
enforce_eager	Disable CUDA graph optimization	false
enable_chunked_prefill	Enable chunked prefill for long contexts	false
tensor_parallel_size	Tensor parallelism degree	1
disable_tqdm	Disable progress bar for rollouts	false
max_num_batched_tokens	Maximum tokens in batch for vLLM	12288
<i>Validation Override</i>		
val_override_config.temperature	Temperature for validation rollouts	1.0
val_override_config.top_p	Top-p for validation rollouts	0.7
val_override_config.n	Number of validation rollouts	16

Table 7: Rollout worker hyperparameters for vLLM-based generation.

Parameter	Description	Default Value
<i>FSDP Configuration</i>		
enable_full_shard	Enable full parameter sharding	true
enable_cpu_offload	Offload reference model to CPU	true
enable_rank0_init	Initialize only on rank 0	true
<i>Memory Offload</i>		
offload_params	Offload model parameters	false

Table 8: Reference model worker hyperparameters.

Parameter	Description	Default Value
reward_type	Reward computation mode (options: batch, online)	batch

Table 9: Reward model worker hyperparameters.

Parameter	Description	Default Value
total_epochs	Total number of training epochs	10
max_steps	Maximum training steps (overrides epochs if set)	<i>not set</i>
project_name	Project name for logging	<i>User-defined</i>
experiment_name	Experiment identifier	<i>User-defined</i>
logger	Logging backends to use	[console, wandb, swanlab]
nnodes	Number of compute nodes	1
n_gpus_per_node	GPUs per node	4
max_try_make_batch	Maximum batch creation retries	10
val_freq	Validation frequency (epochs)	5
val_before_train	Run validation before training	true
val_only	Run validation only (no training)	false
val_generations_to_log	Number of validation examples to log	3
save_freq	Checkpoint saving frequency (steps)	20
save_limit	Maximum checkpoints to keep	3
save_model_only	Save only model weights (no optimizer)	false
save_checkpoint_path	Directory for saving checkpoints	<i>User-defined</i>
load_checkpoint_path	Path to load checkpoint from	null
find_last_checkpoint	Auto-resume from last checkpoint	true

Table 10: Training orchestration hyperparameters.