

# Efficient Reinforcement Learning from Human Feedback via Bayesian Preference Inference<sup>\*</sup>

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**Abstract:** Learning from human preferences is a cornerstone of aligning machine learning models with subjective human judgments. Yet, collecting such preference data is often costly and time-consuming, motivating the need for more efficient learning paradigms. Two established approaches offer complementary advantages: RLHF scales effectively to high-dimensional tasks such as LLM fine-tuning, while PBO achieves greater sample efficiency through active querying. We propose a hybrid framework that unifies RLHF’s scalability with PBO’s query efficiency by integrating an acquisition-driven module into the RLHF pipeline, thereby enabling active and sample-efficient preference gathering. We validate the proposed approach on two representative domains: (i) high-dimensional preference optimization and (ii) LLM fine-tuning. Experimental results demonstrate consistent improvements in both sample efficiency and overall performance across these tasks.

**Keywords:** Human-in-the-Loop optimization; Reinforcement Learning from Human Feedback (RLHF); Preferential Bayesian Optimization (PBO); Active learning; Preference-based optimization; Large Language Models (LLMs); High-dimensional optimization.

## 1. INTRODUCTION

Many real-world problems involve objectives that are difficult to specify explicitly but easy for humans to recognize intuitively. In such settings, humans can reliably state which of two outcomes is preferable, even when they cannot articulate a quantitative function that captures this preference. For instance, in vehicle suspension tuning, ride comfort is a subjective criterion that cannot be directly encoded as a quantitative cost function, yet a human can easily express which suspension configuration provides a better experience. This gap between human intuition and mathematical formalization has motivated the development of frameworks that learn directly from human feedback, allowing models to approximate subjective notions of quality without requiring explicit reward definitions.

In optimization and control, it is often referred to as preference-based optimization, where the objective function is implicit and only pairwise comparisons are available. Methods such as Preferential Bayesian Optimization (PBO) (Chu and Ghahramani (2005); Brochu (2010); González et al. (2017); Benavoli et al. (2023)) model latent utilities using Gaussian Processes (GPs) and leverage acquisition functions to actively select informative comparisons. While sample-efficient, GP surrogates scale poorly

in high dimensions.

In contrast, within the reinforcement learning community, preference feedback has emerged under the paradigm of Reinforcement Learning from Human Feedback (RLHF) (Christiano et al. (2017)). By training a reward model from pairwise human judgments and optimizing it through reinforcement learning, RLHF has become a key component in aligning large language models (LLMs) with human expectations (Ziegler et al. (2019)). However, standard RLHF is data-hungry, which is problematic when annotation budgets are limited.

To mitigate this, recent works have begun exploring active preference learning strategies that aim to select the most informative comparisons. For instance, Sekhari et al. (2023) studied query complexity in preference-based reinforcement learning, while Ji et al. (2024) introduced Active Proximal Policy Optimization (APPO) for linear dueling bandits with provable suboptimality bounds. Other efforts have incorporated query costs directly into the reward formulation (Schulze and Evans (2018); Krueger et al. (2020); Tucker et al. (2023)), highlighting a growing interest in integrating efficiency considerations into human-feedback loops.

In this work, we introduce a hybrid framework that combines the query efficiency of preference-based optimization with the scalability of learning from human feedback, thereby bridging the gap between classical PBO and modern RLHF. Compared to PBO, the proposed approach leverages neural reward models, as in RLHF, and therefore does not suffer from the scalability limitations that arise when using Gaussian Process surrogates in high-dimensional settings. Relative to standard

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RLHF, it introduces a Bayesian acquisition mechanism that actively selects informative preference queries, substantially improving data efficiency under constrained annotation budgets. Unlike recent efforts to enhance RLHF through ensemble- or logit-based uncertainty approximations, our method employs a Laplace-based Bayesian estimation that provides a theoretically grounded and computationally lightweight measure of model uncertainty, which can be seamlessly integrated into existing RLHF training pipelines. The resulting framework, referred to as **Bayesian RLHF**, operates seamlessly across domains—from fine-tuning large language models to optimizing high-dimensional continuous functions, and consistently outperforms RLHF and PBO in both sample efficiency and accuracy. The main contributions of this work are as follows:

- We incorporate a **Laplace-based Bayesian uncertainty estimation** within the RLHF pipeline, providing a principled means of uncertainty quantification without relying on costly ensembles or heuristic logit-based approximations.
- Building upon Dueling Thompson Sampling, we introduce a **mixing acquisition strategy** that balances exploration and exploitation through a fixed mixing coefficient, enhancing sample efficiency while preserving scalability to high-dimensional neural settings.
- We validate the proposed framework on two complementary domains, high-dimensional numerical optimization and LLM fine-tuning from human preferences, demonstrating consistent improvements in both **sample efficiency** and **final performance**.

## 2. PRELIMINARIES

### 2.1 Reinforcement Learning from Human Feedback (RLHF)

Reinforcement Learning from Human Feedback (RLHF) (Christiano et al. (2017)) is a framework designed to align policy behavior with human preferences through an iterative loop involving data collection, reward modeling, and policy optimization. In its standard formulation, RLHF starts from a pretrained policy  $\pi_\theta$ , typically a neural network or a language model, that generates candidate outputs for a given input. Human evaluators then provide pairwise comparisons between outputs, indicating which is preferred. These comparisons are used to train a reward model  $r_\phi(x, y)$ , typically a neural network, that predicts the relative preference between two outputs  $y_1$  and  $y_2$  conditioned on an input  $x$ :

$$P(y_1 \succ y_2 | x) = \sigma(r_\phi(x, y_1) - r_\phi(x, y_2)), \quad (1)$$

where  $\sigma(\cdot)$  denotes the logistic function.

The trained reward model, then guides policy optimization, typically via PPO (Schulman et al. (2017)).

While RLHF has demonstrated remarkable success in aligning large language models with human intent, its data collection process remains a critical bottleneck. In the original formulation, query selection relies on estimating uncertainty in the reward model by maintaining an ensemble of predictors and sampling those comparisons that yield the highest disagreement among ensemble members. Although this approach provides a rough measure of uncertainty, it represents only a crude approximation of optimal

information gain. The authors themselves noted that, in some tasks, this strategy even degraded performance.

### 2.2 Preferential Bayesian Optimization (PBO)

Preferential Bayesian Optimization (PBO) (Chu and Ghahramani (2005); Brochu (2010); González et al. (2017); Benavoli et al. (2023)) extends the principles of Bayesian Optimization (BO) to settings where the objective function is unknown and can only be queried through pairwise preferences rather than scalar evaluations. Given two candidate solutions  $\mathbf{x}_1$  and  $\mathbf{x}_2$ , the human provides a preference  $\mathbf{x}_1 \succ \mathbf{x}_2$  if  $\mathbf{x}_1$  is judged better. These comparisons are modeled by a latent utility function  $f(\mathbf{x})$ , endowed with a Gaussian Process (GP) prior. The likelihood of a preference is modeled via a Bernoulli distribution:

$$P(\mathbf{x}_1 \succ \mathbf{x}_2) = \Phi\left(\frac{f(\mathbf{x}_1) - f(\mathbf{x}_2)}{\sqrt{2}\sigma}\right), \quad (2)$$

where  $\Phi$  is the cumulative Gaussian function and  $\sigma$  represents observation noise.

At each iteration, PBO uses the GP posterior to compute an acquisition function  $a(\mathbf{x})$  that quantifies the expected utility of querying a given point.

$$(\mathbf{x}_i, \mathbf{x}_j) = \arg \max_{\mathbf{x}_i, \mathbf{x}_j} a(\mathbf{x}_i, \mathbf{x}_j) \quad (3)$$

where  $a$  aims to maximize expected information gain about  $f$ , or equivalently, reduce posterior uncertainty. This active querying mechanism enables PBO to focus human feedback on the most informative comparisons, dramatically improving sample efficiency. However, the reliance on Gaussian Process priors causes the computational cost and memory footprint to scale poorly with both the number of dimensions and the number of observations, making it less suitable for large-scale or high-dimensional problems such as LLM fine-tuning.

### 2.3 Laplace Approximation

The *Laplace Approximation* (LA) is a classical Bayesian technique that approximates the posterior distribution of a model’s parameters without requiring architectural changes or ensembles of networks. Conceptually, LA constructs a local Gaussian approximation of the posterior distribution centered at the most probable parameters of the model.

From a Bayesian perspective, minimizing a regularized loss function can be interpreted as finding the *maximum-a-posteriori* (MAP) estimate:

$$\theta_{\text{MAP}} = \arg \min_{\theta} \mathcal{L}(\mathcal{D}; \theta), \quad (4)$$

where  $\mathcal{L}(\mathcal{D}; \theta)$  denotes the loss computed over the dataset  $\mathcal{D}$ .

The Laplace approximation replaces the original loss with its second-order Taylor expansion around  $\theta_{\text{MAP}}$ :

$$\begin{aligned} \mathcal{L}(\mathcal{D}; \theta) &\approx \mathcal{L}(\mathcal{D}; \theta_{\text{MAP}}) + \frac{1}{2}(\theta - \theta_{\text{MAP}})^\top H(\theta - \theta_{\text{MAP}}), \\ H &= \nabla_{\theta}^2 \mathcal{L}(\mathcal{D}; \theta) \Big|_{\theta=\theta_{\text{MAP}}}. \end{aligned} \quad (5)$$

Since the expansion is performed around the minimum point  $\theta_{\text{MAP}}$ , the first-order term vanishes. After standard

algebraic manipulations, it can be shown that the posterior distribution can be approximated as:

$$P(\theta | \mathcal{D}) \approx \mathcal{N}(\theta_{\text{MAP}}, H^{-1}), \quad (6)$$

which implies that, after training, the posterior distribution of the parameters is Gaussian centered at the MAP estimate and with covariance given by the inverse Hessian. Thus, a deterministic network gains a local Gaussian posterior over parameters.

### 3. MAIN CONTRIBUTION

This section introduces the proposed hybrid framework, termed Bayesian RLHF. As illustrated in Fig. 1, our approach introduces two key additions to the classical RLHF loop: (i) a *Laplace-based uncertainty estimation* in the reward model, and (ii) an *acquisition function* that exploits this uncertainty to actively guide human queries. Both extensions are lightweight and compatible with existing RLHF frameworks, such as Hugging Face `tr1` (von Werra et al. (2020)). The Laplace approximation is applied *post hoc* to a pre-trained reward model, without requiring any modification to the training pipeline or architecture.

#### 3.1 Laplace-Based Reward Model

In classical RLHF, the reward model  $r_\phi$  is trained via maximum likelihood on pairwise preferences  $(y_1, y_2)$  to approximate the human-judged preference probability:

$$P(y_1 \succ y_2 | x) = \sigma(r_\phi(x, y_1) - r_\phi(x, y_2)), \quad (7)$$

where  $\sigma(\cdot)$  denotes the logistic link. This formulation corresponds to a *binary classification task* with discrete feedback, where the model learns to predict the preferred output between two alternatives. However, standard training yields only a point estimate  $\phi_{\text{MAP}}$  of the reward parameters, providing no notion of uncertainty about the learned preferences. To endow the reward model with calibrated uncertainty estimates, we apply the Laplace Approximation (Daxberger et al. (2021)). First, the reward model is trained to obtain the  $\phi_{\text{MAP}}$ . The second step consists of computing the Hessian matrix  $H$ , which captures the local curvature of the loss around  $\phi_{\text{MAP}}$ . Nevertheless, using LA within an iterative framework such as RLHF introduces several challenges: (1) Computing the Hessian requires a full pass over the fine-tuning dataset, which continually grows during training. (2) Storing the Hessian is infeasible, as its size scales quadratically with the number of parameters (which are typically very large in the context of LLMs). (3) Evaluating the Hessian can be computationally prohibitive, and the resulting matrix may be indefinite.

To overcome these limitations, instead of resorting to large-scale approximations (e.g., Fisher information or diagonalized Hessians), we adopt a more practical strategy: compute the exact Hessian only for a small subset of parameters, typically those in the final layer of the network. This approach, commonly referred to as the last-layer Laplace approximation, allows the method to scale efficiently to large models. In the context of RLHF with an LLM-based reward model, this corresponds to the compact classification head (approximately 512 parameters) attached to the frozen language model backbone.

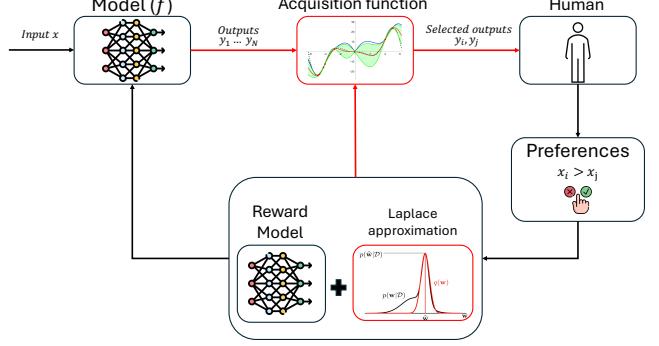


Fig. 1. Overview of the proposed Bayesian RLHF framework, integrating Laplace-based uncertainty estimation in the reward model and an acquisition function for efficient preference querying. Novel components relative to standard RLHF are highlighted in red.

#### 3.2 Acquisition-Driven Query Selection

While the Laplace approximation endows the reward model with calibrated uncertainty estimates, the next step is to exploit this uncertainty to actively select informative preference queries. Therefore, we introduce an *acquisition-driven query selection* mechanism inspired by PBO. Our strategy is based on *Dueling Thompson Sampling* (DTS), an acquisition function that explicitly balances exploration and exploitation. At each iteration, a set of candidate responses  $\{y_i\}_{i=1}^M$  is evaluated by the Bayesian reward model, producing both mean and variance estimates of their scores. The *best* candidate  $y_{\text{best}}$  is chosen as the one with the highest sampled utility from the posterior distribution, and a *rival* candidate  $y_{\text{rival}}$  is then selected according to one of two complementary modes.

**Sparring Mode — Exploitation.** In this mode, the rival is sampled stochastically among strong candidates to favor duels likely to refine the current preference boundary. Let  $s(y_i)$  denote the predicted win score for candidate  $y_i$ ; the rival is drawn from a softmax distribution controlled by a temperature  $T$ :

$$y'_{\text{rival, spar}} \sim \text{Softmax}\left(\frac{s(y_i)}{T}\right), \quad (8)$$

where lower  $T$  values emphasize exploitation by amplifying score differences, while higher  $T$  promotes broader sampling.

**MaxVar Mode — Exploration.** Conversely, in the *MaxVar* mode the rival is chosen as the candidate inducing the highest predictive uncertainty with respect to the current best:

$$y'_{\text{rival, maxvar}} = \arg \max_{y_i \in \mathcal{Y}} \text{Var}[p(y_{\text{best}} \succ y_i)], \quad (9)$$

where  $\text{Var}[p(\cdot)]$  denotes the posterior variance of the win probability estimated via the Laplace-based reward model. This encourages duels that are maximally informative for refining the model’s belief, thereby encouraging exploration of uncertain regions in the preference space.

**Mixed Strategy — Balancing Exploration and Exploitation.** To flexibly navigate between exploration and

exploitation, we introduce a *convex combination* of the two modes. The acquisition score  $J_\alpha(y')$  for a candidate  $y'$  is defined as:

$$J_\alpha(y') = \alpha \frac{S_{\text{spar}}(y') - \mathbb{E}[S_{\text{spar}}]}{\text{Std}[S_{\text{spar}}]} + (1-\alpha) \frac{S_{\text{var}}(y') - \mathbb{E}[S_{\text{var}}]}{\text{Std}[S_{\text{var}}]}. \quad (10)$$

where  $\alpha \in [0, 1]$  controls the trade-off between the exploitation-oriented Sparring score and the exploration-oriented MaxVar score. For  $\alpha = 1$ , the system prioritizes refinement of strong candidates (Sparring), while  $\alpha = 0$  targets uncertain duels to expand the learned preference space (MaxVar).

The proposed acquisition-driven query selection transforms RLHF from a passive preference learner into an *active querying framework*.

### 3.3 Theoretical Motivation.

Before presenting the experimental results, it is worth highlighting that the proposed hybrid Bayesian RLHF method inherits theoretical advantages over classical PBO in high-dimensional settings. Compared to Gaussian-process-based PBO, the proposed Bayesian RLHF framework achieves:

- (1) **Improved scalability.** The cumulative regret of PBO is governed by the information gain term, which, as demonstrated by Srinivas et al. (2012), grows rapidly with the dimensionality of the input space. This results in an exponential increase in the number of queries required to reach comparable performance as the problem dimension increases, making GP-based methods impractical in high-dimensional spaces.
- (2) **Reduced computational complexity.** In PBO, posterior updates over the latent preference function require approximate inference. When the Laplace approximation is employed, the dominant computational cost arises from cubic matrix operations,  $\mathcal{O}(T^3)$ , with respect to the number of queries  $T$ . In contrast, the proposed Bayesian RLHF method applies the Laplace approximation only to the final layer of the neural reward model, which typically contains a small and fixed number of parameters.

These theoretical considerations suggest that the proposed hybrid Bayesian RLHF method maintains the expressiveness and scalability of neural models while retaining the uncertainty quantification benefits of Laplace-based Bayesian inference.

## 4. EXPERIMENTAL RESULTS

This section presents a numerical evaluation of the proposed Bayesian RLHF (B-RLHF) on (i) numerical optimization against PBO and (ii) LLM fine-tuning compared to RLHF.

### 4.1 High-Dimensional Preference Optimization

The optimization task is based on the  $d$ -dimensional Rosenbrock function, a nonlinear benchmark characterized by a narrow, curved valley that makes both exploration

and convergence particularly challenging.

For this experiment, we implemented the two algorithms as follows:

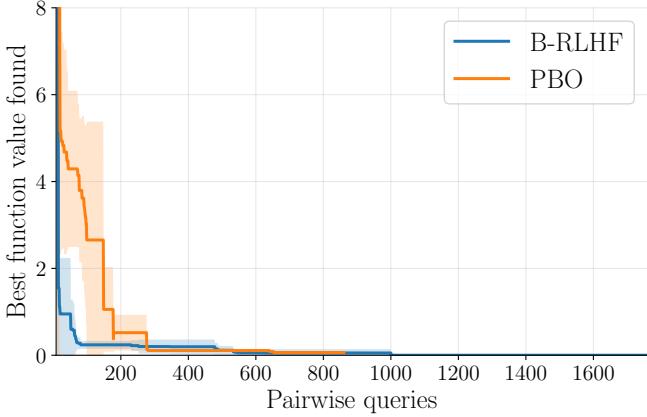
- **Bayesian RLHF:** both the policy and reward models are implemented as neural networks. The reward model is trained from pairwise comparisons using a Bradley–Terry logistic loss and consists of a deep multilayer perceptron (MLP) backbone with a linear head. A Laplace approximation is applied to the last layer. The acquisition function parameter  $\alpha$  (see Eq. 10) is set equal to 0.5 to balance exploration and exploitation.
- **PBO:** we implemented a Matérn kernel PBO baseline that employs Laplace-based uncertainty estimation.

All experiments were executed on identical hardware (Intel Xeon 2.00 GHz CPU, 13 GB RAM, NVIDIA Tesla P100 GPU with 16 GB VRAM) to ensure fairness. Uniform stopping criteria were enforced: (i) a computational budget proportional to the problem dimensionality (larger dimensions implying larger budgets), and (ii) a fixed wall-clock time limit of 10 hours.

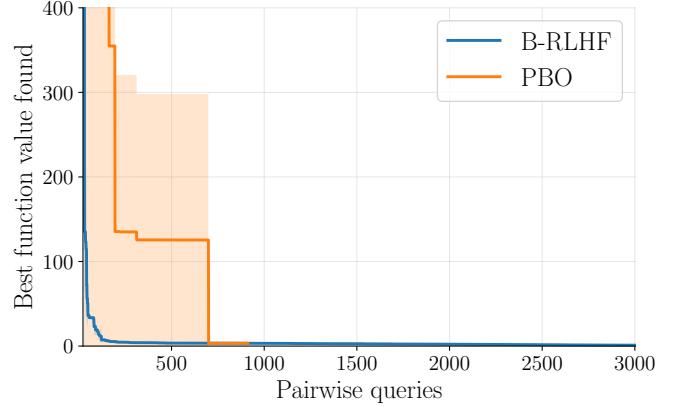
Figure 2a compares our Bayesian RLHF method with PBO on the 2D Rosenbrock problem across 5 Monte Carlo runs. Our approach achieves faster convergence, and reaches a 44% lower error on average at the final iteration. The Bayesian RLHF fully exploited the available queries budget within the time limit, whereas the baseline PBO required significantly longer runtime, completing on average only 850 preference queries within the same time limit, which is consistent with its theoretical cubic complexity in the number of queries as discussed in Section 3.3. Similar trends are observed in the 5D case (Figure 2b), where Bayesian RLHF exhibits superior convergence speed and solution quality, reaching the final error achieved by PBO 200 queries earlier while using only 20% of the full query budget.

Figure 3 extends the comparison to high-dimensional settings (10D and 50D Rosenbrock). In the 10D case, PBO failed to complete the optimization due to memory exhaustion after 650 queries, while our method successfully converged within the full query budget of 4000. Figure 4 reports the final absolute error at termination for both methods, further underscoring the superiority of our approach. At 50 dimensions, PBO becomes computationally infeasible, whereas Bayesian RLHF, Figure 3b, continues to make progress throughout the 10-hour window, demonstrating a consistent convergence trend despite not fully exhausting the budget.

Finally, in this numerical optimization setting, we performed a sensitivity analysis of the  $\alpha$  parameter controlling the exploration-exploitation balance in our acquisition function. The results are shown in Figure 5. We performed 38 Monte Carlo runs on the 2D Rosenbrock function, varying  $\alpha$  from 0 (pure max-variance exploration) to 1 (pure exploitation). Results indicate that intermediate values of  $\alpha$  yield the most sample-efficient optimization, requiring the fewest preference queries to reach the optimum, highlighting the benefit of a mixed exploration-exploitation strategy. In this experiment, the best-performing value of  $\alpha$  was 0.5, which achieved the lowest median and interquartile range of queries required to reach the optimum.

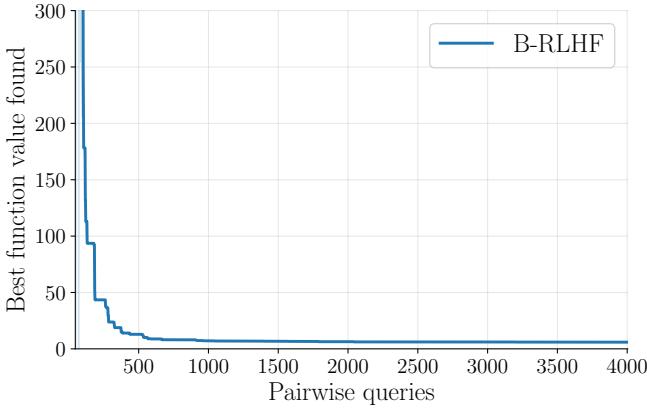


(a) 2D Rosenbrock optimization.

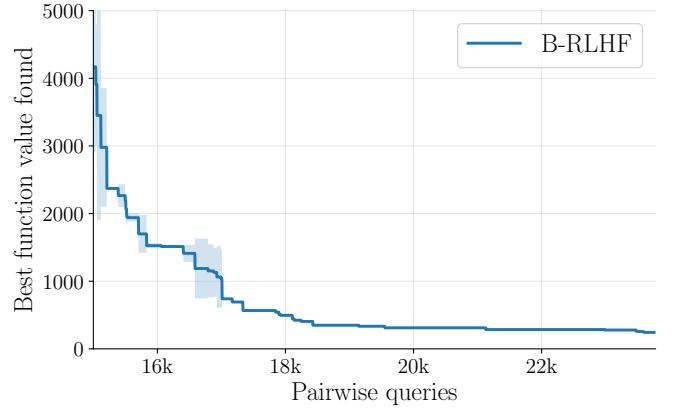


(b) 5D Rosenbrock optimization.

Fig. 2. Comparison between Bayesian RLHF (B-RLHF) in blue and baseline PBO in orange on the Rosenbrock problem. Solid lines indicate the mean response, and the shaded bands represent  $\pm$  one standard deviation over 5 Monte Carlo runs.



(a) 10D Rosenbrock optimization.



(b) 50D Rosenbrock optimization.

Fig. 3. Best value of the latent function on the Rosenbrock optimization problem, achieved by our algorithm Bayesian RLHF (B-RLHF). Solid lines indicate the mean response, and the shaded bands represent  $\pm$  one standard deviation over 3 Monte Carlo runs.

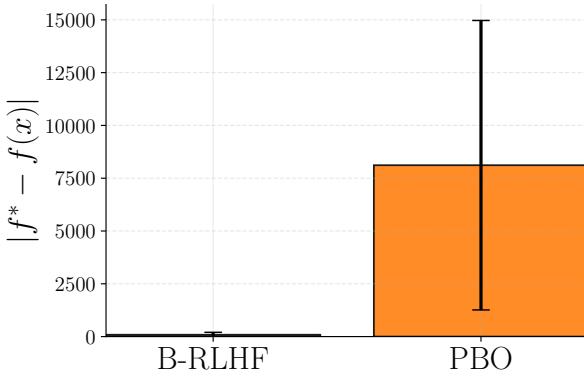


Fig. 4. Mean and standard deviation of the final optimization error across 3 independent runs for B-RLHF and PBO on the 10D Rosenbrock function with a budget of 4000 queries, a 10-hour time limit.

#### 4.2 LLM Fine-Tuning

To further validate our approach, we extend the analysis to a language-model fine-tuning scenario based on human

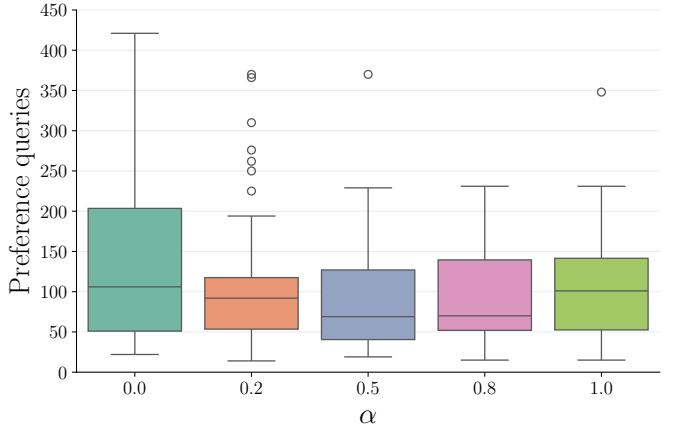


Fig. 5. Sensitivity analysis of the  $\alpha$  exploration-exploitation parameter, averaged over 38 Monte Carlo runs.

preferences. We derive both the base and reward net-

works from the Pythia-70M<sup>1</sup> architecture and trained on the publicly available Dahoas/rm-hh-rlhf<sup>2</sup> dataset. Each record contains a user prompt and two candidate assistant responses, where the one labeled as “*chosen*” reflects the human-preferred completion over the “*rejected*” one. The dataset comprises approximately 112K training and 12.5K test samples within the Helpful & Harmless (HH) dialogue preference framework. For each training iteration, prompts are sampled from the static Dahoas/rm-hh-rlhf dataset, while the corresponding candidate responses are generated online by the policy model. In the baseline RLHF configuration, two responses are sampled uniformly from the model outputs, following the standard approach used in Ziegler et al. (2019). In contrast, our Bayesian RLHF implementation employs an uncertainty-based acquisition function to select the response pair expected to be most informative according to the reward model. This setup reproduces an online active preference selection process, where querying decisions depend dynamically on model uncertainty rather than uniform sampling. Following established RLHF literature (Eisenstein et al. (2023); Coste et al. (2023); Shen et al. (2024)), we employed *PairRM* (Jiang et al. (2023)) as a proxy human annotator, a reward model trained on the large-scale UltraFeedback<sup>3</sup> dataset, which encompasses the HH dataset and is renowned for its diversity and high-quality annotations. All experiments were conducted on identical hardware equipped with an NVIDIA A100 GPU featuring 32 GB of VRAM.

Since the reward model is the principal component modified in our framework and serves as a proxy for human feedback during policy optimization, we focus our evaluation on its **predictive accuracy**. The reward model was fine-tuned with the last two layers unfrozen, corresponding to approximately 6 million parameters (16% of the total), using a learning rate of  $6 \times 10^{-4}$ . The model parameters were updated every 200 preference queries. Results in table 1 compares our Bayesian RLHF method with the baseline RLHF on the LLM fine-tuning task, averaged over three Monte Carlo runs. In this setting, we used 1,400 pairwise preferences for training and 500 unseen prompts for testing. All configurations of our method (for all tested values of  $\alpha$ ) achieved higher final accuracy than the baseline RLHF. In particular, Figure 6 compares the best-performing configuration ( $\alpha = 0.5$ ) against the baseline, showing a **6% improvement in mean accuracy**. An additional experiment performed with an increased preference budget is summarized in Table 2. The best-performing configuration ( $\alpha = 1$ ) achieved a **14% improvement** over standard RLHF. Interestingly, with the larger preference budget, the optimal configuration shifted from  $\alpha = 0.5$  to  $\alpha = 1$ . This behavior can be explained by the reduced uncertainty of the reward model at higher data volumes: once the model achieves sufficient predictive accuracy, exploration offers diminishing returns, and a purely exploitative strategy becomes more effective in driving convergence.

Across both experiments, our Bayesian RLHF method consistently outperformed standard RLHF. Notably, even with a limited number of pairwise queries (at most 3.1% of the available dataset), the method demonstrated robust

improvements. We deliberately constrained the query budget for two reasons:

- (1) To emulate realistic human-in-the-loop settings, where preference collection is expensive.
- (2) To shorten training time and emphasize sample efficiency.

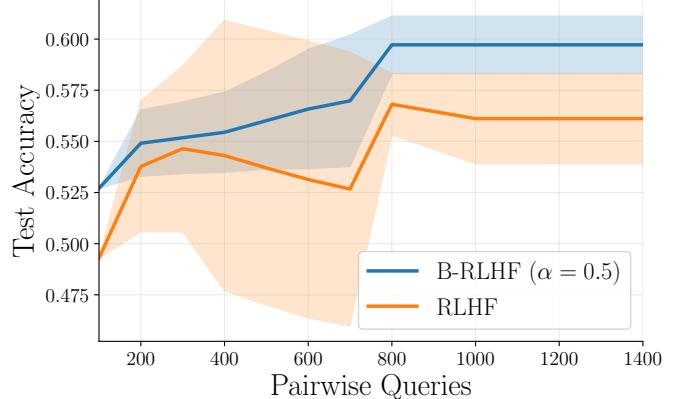


Fig. 6. Comparison between Bayesian RLHF (B-RLHF) with  $\alpha = 0.5$ , which achieved the best overall accuracy across all tested  $\alpha$  values, and the baseline RLHF on the LLM fine-tuning problem. Solid lines denote the mean performance, and shaded regions indicate  $\pm$  one standard deviation over three Monte Carlo runs.

Table 1. Test-set accuracy for Bayesian RLHF (B-RLHF) and baseline RLHF on the LLM fine-tuning task, averaged over three Monte Carlo runs. Each run uses 1,400 training and 500 testing preference queries. Reported values correspond to the accuracy at the final iteration, with mean and standard deviation computed across 3 Monte Carlo runs.

| Method | $\alpha$ | Mean         | Std.   |
|--------|----------|--------------|--------|
| B-RLHF | 0        | 0.596        | 0.001  |
| B-RLHF | 0.2      | 0.585        | 0.008  |
| B-RLHF | 0.5      | <b>0.597</b> | 0.014  |
| B-RLHF | 0.8      | 0.577        | 0.0261 |
| B-RLHF | 1        | 0.593        | 0.001  |
| RLHF   | -        | 0.561        | 0.022  |

Table 2. Test-set accuracy of the Bayesian RLHF (B-RLHF) and baseline RLHF models on the LLM fine-tuning task, trained with an extended dataset comprising 3,500 training and 1,000 testing preference queries. Results are reported from a single run and correspond to the accuracy at the final iteration.

| Method | $\alpha$ | Accuracy     |
|--------|----------|--------------|
| B-RLHF | 0        | 0.587        |
| B-RLHF | 0.2      | 0.589        |
| B-RLHF | 0.5      | 0.616        |
| B-RLHF | 0.8      | 0.615        |
| B-RLHF | 1        | <b>0.635</b> |
| RLHF   | -        | 0.549        |

<sup>1</sup> <https://huggingface.co/EleutherAI/pythia-70m>

<sup>2</sup> <https://huggingface.co/datasets/Dahoas/rm-hh-rlhf>

<sup>3</sup> <https://huggingface.co/datasets/openbmb/UltraFeedback>

## 5. CONCLUSIONS

This paper introduced *Bayesian RLHF*, a hybrid framework that combines the sample-efficiency benefits of preference-based optimization with the scalability of learning from human feedback. Across both numerical optimization and language-model fine-tuning tasks, the proposed approach demonstrated faster convergence and higher test accuracy under tight query budgets, supporting our central claim on data efficiency.

The present study is limited by the evaluation scope, which primarily assessed reward-model accuracy using a proxy annotator. Extending the analysis to full end-to-end policy optimization with human raters represents an important direction for future work.

Future research will also investigate an adaptive exploration-exploitation trade-off within the acquisition mechanism, as well as the use of the proposed uncertainty quantification in the policy optimization step to further enhance stability and performance.

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