DRLC: Reinforcement Learning with Dense Rewards from LLM Critic

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Abstract

Reinforcement learning (RL) can align language models with non-differentiable reward signals, such as human preferences. However, a major challenge arises from the sparsity of these reward signals - typically, there is only one reward for the entire generation. This sparsity of rewards can lead to inefficient and unstable learning. In this paper, we introduce a novel framework leveraging the critique ability of LLMs to produce dense rewards throughout the learning process. Our approach incorporates a critic language model alongside the policy model. This critic is prompted with the task description, question, policy model's output, and environment's reward signal as input, and provides token or span-level dense rewards that reflect the quality of each segment of the output. We assess our approach on three text generation tasks: sentiment control, language model detoxification, and summarization. Experimental results show that incorporating artificial dense rewards in training yields consistent performance gains over the PPO baseline with holistic rewards. Furthermore, in a setting where the same model serves as both policy and critic, we demonstrate that "self-critique" rewards also boost learning efficiency.

1 Introduction

Large language models (LLMs) have seen a rapid advancement in recent years, demonstrating a remarkable ability to understand and generate natural language (Brown et al., 2020b; Touvron et al., 2023; OpenAI, 2023; Biderman et al., 2023; Jiang et al., 2023). In the meanwhile, reinforcement learning has emerged as a complementary tool for further refining the capabilities of LMs. By leveraging the power of RL, models can be optimized toward any non-differential reward signal. For example, techniques like reinforcement learning from human feedback (RLHF) (Ziegler et al., 2019; Stiennon

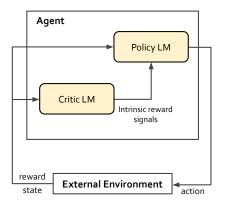


Figure 1: Illustration of the proposed framework. There are two modules inside the agent. The critic LM takes the state and reward as input and generates dense intrinsic reward signals that evaluate different parts of the generation. The policy module is trained to optimize the weighted sum of intrinsic and extrinsic rewards.

et al., 2020) have been used to steer language models to align with human preferences, thus enabling more complex and nuanced behavior from LMs.

However, rewards extrinsic to the agent are usually sparse, a fundamental bottleneck that restricts the efficiency of learning (Andrychowicz et al., 2017; Sukhbaatar et al., 2018). Typically, in text generation tasks, a single scalar reward is obtained after a sentence or paragraph has been fully generated. This single reward signal introduces a temporal credit assignment problem, making it difficult for the model to determine which words were responsible for the received reward, hindering efficient learning. Previous attempts to circumvent the sparsity of rewards in RL have included reward shaping (Ng et al., 1999; Devidze et al., 2022; Goyal et al., 2019), curiosity-driven exploration (Bellemare et al., 2016; Pathak et al., 2017a; Ostrovski et al., 2017), and hierarchical RL (Nachum et al., 2018; Zhang et al., 2021). However, these methods either require handcrafted features or do not translate straightforwardly into the domain of language generation. Recent studies, such as those

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by Lightman et al. (2023) and Wu et al. (2023), have investigated the use of human annotators to provide detailed feedback. However, this approach is costly and difficult to scale, making it impractical for extensive text corpora or real-world applications that require rapid iteration.

In light of these limitations, our work is motivated by the potential of leveraging the critique ability of LLMs (Madaan et al., 2023; Saunders et al.; Luo et al., 2023) to generate fine-grained reward signals. As shown in Figure 1, we explicitly define an RL "agent" as the integration of 1) a policy model for language generation, and 2) a critique model that provides dense intrinsic rewards. The critic LM, informed by the task description, the policy model's output, and the extrinsic reward signal provided by the environment, is tasked with generating token or span-level fine-grained rewards. The critic model can either be an pre-trained LLM or the policy model itself. We evaluate the effectiveness of our method through three text generation tasks: sentiment control, LM detoxification, and abstractive summarization. To train the agent, we employ the Proximal Policy Optimization (PPO) algorithm (Schulman et al., 2017). Experimental results show that using LLM generated intrinsic rewards largely improves sample efficiency over traditional holistic reward-based learning methods.

Our contributions are summarized as follows: First, we introduce a novel framework that utilizes the critique capability of LLMs to generate dense intrinsic reward signals. This approach effectively alleviates the temporal credit assignment problem, leading to a substantial improvement in sample efficiency. Our method can be seamlessly integrated into standard RL algorithms, without necessitating any modifications to the algorithms themselves. Second, we evaluate our method on three text generation tasks. Our method outperforms several strong baselines on public benchmarks. Finally, we explore a more challenging setting termed "selfcritique", where the policy and critic models are the same. In this setting, we find that the incorporation of intrinsic rewards still markedly improve sample efficiency. Collectively, these contributions represent a significant step forward in the pursuit of more efficient RL-based text generation methods.

2 Related Work

RL for Text Generation. RL methods have been used in various text generation tasks including text

summarization (Ryang and Abekawa, 2012; Gao et al., 2018; Stiennon et al., 2020; Pang and He, 2021; Cao et al., 2022a; Dong et al., 2018), machine translation (Norouzi et al., 2016; Ranzato et al., 2016; Wu et al., 2016; He et al., 2016; Bahdanau et al., 2017), dialogue systems (Fatemi et al., 2016; Li et al., 2016; Dhingra et al., 2017; Su et al., 2017; Peng et al., 2017; Jaques et al., 2019) and question answering (Buck et al., 2018; Xiong et al., 2018; Nakano et al., 2021). The application of RL to these tasks has led to improved performance and better generalization over traditional supervised learning methods. Recent studies have focused on combining RL with pre-trained language models like GPT-3 (Brown et al., 2020a) to generate text (Ouyang et al., 2022; Bai et al., 2022; Nakano et al., 2021; Stiennon et al., 2020) are better aligned with human preference such as being factual, relevant and helpful.

Reward Shaping and Intrinsic Rewards. Ng et al. (1999) laid the groundwork for potentialbased reward shaping in RL, demonstrating that such shaping can effectively reduce training time without changing the optimal policy. This concept has inspired subsequent research in augmenting learning processes through auxiliary rewards. Notably, studies by Bellemare et al. (2016); Ostrovski et al. (2017); Tang et al. (2017) have employed pseudo-count-based rewards to encourage exploration in environments where rewards are sparse. Pathak et al. (2017b) use the agent's prediction errors as intrinsic reward signals to encourage exploration. Zheng et al. (2018) proposed a method where a parameterized intrinsic reward model is learned during training to generate dense reward signals. This approach, however, presents certain optimization difficulties due to the necessity of calculating second-order gradients. Wu et al. (2023); Anonymous (2023) employ human annotators to provide detailed span-level reward signals, demonstrating that these fine-grained rewards yield better performance compared to holistic rewards.

LLM for Reward Design. Recent advancements in LLMs have opened new avenues in reward design for RL. For instance, Lee et al. (2023) employed an off-the-shelf LLM to create preference labels by comparing pairs of candidate responses. These labels were then used to train a reward model. Similarly, Klissarov et al. (2023) utilized LLMs to extract preferences between pairs of captions in the

NetHack game (Küttler et al., 2020), using these preferences to train an additional reward function that addresses the challenge of sparse reward signals in the environment. Similarly, (Du et al., 2023) use LLMs to generate intrinsic rewards signals to encourage exploration of the agent. Kwon et al. (2023) investigated the use of GPT-3 as an alternative to the actual reward function in RL training. Their method outperformed the reward model trained through supervised learning, yet it did not achieve the effectiveness of the true reward function. Ma et al. (2023) employed GPT-4 to generate code for a reward function, using the environment's source code and a language task description as context.

3 Method

The basic idea behind our method is to leverage LLM to generate dense intrinsic reward $r^{\rm in}$ and provide it to an RL agent, which will optimize a combination of the intrinsic and extrinsic rewards. In this section, we first establish the Markov decision process (MDP) for text generation. Then, we discuss the policy gradient-based RL method which is widely used for text generation tasks. Finally, we detail the process of incorporating LLM-generated intrinsic rewards into RL training.

3.1 RL for Text Generation

Let us consider the language generation procedure as a MDP (Puterman, 1994), defined by the tuple (S, A, P, R, γ) . Here, S represents the set of all possible states, A is the set of actions, $\mathcal{P}: \mathcal{S} \times \mathcal{A} \times \mathcal{S} \mapsto [0,1]$ is the state transition function, $R: \mathcal{S} \times \mathcal{A} \times \mathcal{S} \mapsto \mathbb{R}$ is the reward function assigning a numerical value to each transition (s, a, s'), and $\gamma \in [0, 1]$ is the discount factor. In the context of text generation, we operate under the assumption of an episodic, discrete-actions, RL setting. The input prompt $s_0 \in \mathcal{S}$ sets the starting state. At each decoding step t, the state $s_t \in \mathcal{S}$ consists of the prompt and the concatenation of the previously generated tokens. Choosing an action involves selecting a token from the vocabulary, leading to a new state s_{t+1} , created by appending the selected token to the currently generated partial sentence. The reward for this transition is $r_t = R(s_t, a_t, s_{t+1})$. The agent's policy $\pi_{\theta}(a|s)$, which is a language model parameterized by θ , determines the probability of selecting each action at a given state. The goal of the agent is to maximize

the discounted cumulative reward throughout the trajectory: $J(\theta) = \mathbb{E}_{\tau \sim \pi_{\theta}} \left[\sum_{t=0}^{T} \gamma^{t} r_{t} \right]$.

3.2 Policy Gradient based RL & PPO

Policy gradient methods are rooted in the principle of gradient ascent. The core idea is to adjust the parameters θ in such a way as to increase the expected return $J(\theta)$, which is defined as the sum of rewards obtained by following the policy over time. The Policy Gradient Theorem (Sutton et al., 1999) provides the foundation for policy gradient methods by giving an explicit expression for $\nabla_{\theta}J(\theta)$. It states that the gradient is proportional to the expectation of the product of the gradient of the log policy and the return G_t :

$$\nabla_{\theta} J(\theta) = \mathbb{E}_{\pi_{\theta}} \left[\nabla_{\theta} \log \pi_{\theta}(a_t | s_t) G_t \right]$$
 (1)

where the return is defined as $G_t = \sum_{i=t}^T \gamma^{i-t} r_i$. A high return leads to the reinforcement of all actions by increasing their selection probability. To reduce variance, a widely adopted strategy involves substituting the raw return G_t in Equation 1 with a generalized advantage estimation function (Schulman et al., 2016):

$$\hat{A}_t = \sum_{t'=t}^{T} (\gamma \lambda)^{t'-t} (r_{t'} + \gamma V(s_{t'+1}) - V(s_{t'})))$$

where λ is a hyper-parameter and $V(s_{t'})$ is the value function representing the expected return at state $s_{t'}$.

Several variants of the basic policy gradient approach have been proposed to improve training stability. One widely used variant, particularly in the context of text generation, is Proximal Policy Optimization (PPO) (Schulman et al., 2017). PPO introduces mechanisms to stabilize the training process by limiting the updates to the policy at each step, effectively preventing destructive large updates that can cause the policy to perform worse. We use the clipped surrogate objective function of PPO which is expressed as:

$$L(\theta) = \hat{\mathbb{E}}_t \Big[\min(r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_t) \Big]$$

where $r_t(\theta) = \frac{\pi_{\theta}(a_t|s_t)}{\pi_{\theta_{\mathrm{old}}}(a_t|s_t)}$ is the probability of taking action a_t at state s_t in the current policy divided by the previous one. We use PPO as the baseline algorithm in this work.

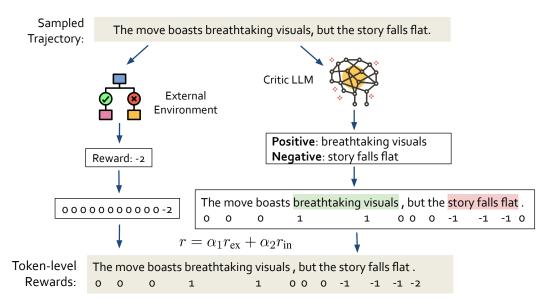


Figure 2: An example demonstrating the reward calculation process in the sentiment control task. In this example, the external environment returns a scalar reward of -2 in response to the policy model's output. Subsequently, the critic model is prompted to identify spans of positive and negative sentiment within the output. Tokens within these spans are then assigned intrinsic rewards: +1 for positive and -1 for negative sentiment. The hyper-parameter α determines the weight of these two types of rewards. The extrinsic reward is assigned to the last position in the output sequence.

3.3 Learning with LLM Generated Intrinsic Rewards

The current RL frameworks for text generation, such as RLHF (Ziegler et al., 2019; Stiennon et al., 2020), the environment takes the entire generated text as input and returns a scalar score. Therefore, the learning typically depends on a sparse reward signal that becomes accessible only upon the generation of a complete sentence. We refer to this reward signal as the extrinsic reward r^{ex} and we have $r_{t < T}^{\text{ex}} = 0$. Our method deviates from the existing approaches by differentiating between the extrinsic reward from the environment and an additional intrinsic reward r^{in} generated by LLM. As shown in Figure 1, within the agent, our framework incorporate an additional critic language model alongside the policy model. The task of the critic model is to pinpoint the tokens or segments in the policy's output that directly contribute to receiving the environment's reward. The critic model is fed with a task description D, a set of few-shot examples E, the current state s as determined by the policy model's output, and optionally, the reward r^{ex} received from the environment. For token at step t, if it is part of the identified segment, we assign an non-zero value to the intrinsic reward r_t^{in} . The final reward is defined as the weighted sum of extrinsic and intrinsic rewards: $r(s,a) = \alpha_1 r^{\text{ex}}(s,a) + \alpha_2 r^{\text{in}}(s,a)$

where α_1 and α_2 are hyper-parameters that controls the weight of the reward. Note that extrinsic rewards are only non-zero at the final time step, specifically when t=T. The policy LM is optimized to maximize the combined reward: $J(\theta)^{\text{DRLC}} = \mathbb{E}_{\tau \sim \pi_{\theta}} \left[\sum_{t=0}^{T} \gamma^{t} (\alpha_{1} r^{\text{ex}} + \alpha_{2} r^{\text{in}}) \right]$ where the policy model is parameterized by θ . The critic LM is frozen during training. In our study, we employed the PPO algorithm to train the agent. However, it's worth noting that our framework is versatile and can also be integrated with other reinforcement learning algorithms, such as Advantage Actor-Critic (A2C) (Mnih et al., 2016). An illustration of how rewards are calculated in the sentiment control task is provided in Figure 2.

LLM Choice and Prompting In this work, we employ two language models as critics: gpt-3.5-turbo-0613 and 7B Llama2-Chat (Touvron et al., 2023). The prompt for these critic models is structured in three segments. Firstly, we start by clearly defining the task at hand within the prompt, setting a well-understood framework for the model. Following this, we enumerate a series of steps, guiding the models in their process of assessing responses generated by the policy model. Finally, to aid the critic models in making informed evaluations, we provide a series of carefully selected few-shot examples, culminating with

the presentation of the specific sample that requires assessment. This structured approach ensures a systematic and thorough evaluation by the critic models.

4 Experiments

In this section, we demonstrate that our method outperforms the PPO baseline in three text generation tasks: sentiment control, LM detoxification, and text summarization.

4.1 Sentiment Control

Sentiment control is a widely researched area that focuses on manipulating the emotional tone of text. This capability is crucial, especially in user-facing applications like chatbots or content recommendation systems (Welivita et al., 2021; Herzig et al., 2016).

Experimental setup. For the training process, we make use of the IMDB dataset, comprising 25K movie reviews (Maas et al., 2011), where each review is associated with a binary label indicating its sentiment as either positive or negative. We randomly extract the first 4 to 10 tokens from each review as the prompt and then sample a continuation of up to 20 tokens from the policy model. We use gpt2-large to initialize the policy model. We train the policy model on the training set for one epoch. As for our reward model, we employ a distilled BERT classifier that is trained on the IMDB dataset[†]. For intrinsic reward generation, we use the gpt-3.5-turbo model through OpenAI's API. The prompt and the few-shot examples used for the sentiment control experiment can be found in Appendix A.1.

Following the experimental setup of (Liu et al., 2021; Lu et al., 2022), we employ the OpenWeb-Text (OWT) Corpus dataset (Gokaslan and Cohen, 2019), which contains 100K human-written prompts, for sentiment evaluation. From these prompts, Liu et al. (2021) curated three distinct test sets: *neutral*, *positive*, and *negative*. These sets were created based on the likelihood of the prompt leading to positive or negative continuations. Specifically, the neutral set comprises 5K prompts, each yielding 12 or 13 positive outcomes from a total of 25 continuations generated using GPT2-large. Both the positive and negative sets include 2.5K prompts, consistently producing 25

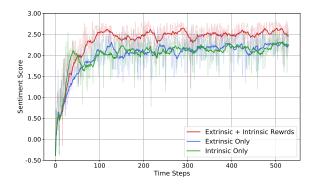


Figure 3: Learning curves of the sentiment control experiment on the IMDB dataset. All three models are trained for one epoch. The x-axis shows the training steps and the y-axis is the logit of the positive class returned by the distilled BERT sentiment classifier. The curves are smoothed using a moving average of 10 to improve readability.

continuations that are either entirely positive or negative, respectively. We conduct out-of-domain evaluation with the *neutral* and *negative* sets.

Baselines and evaluation metrics. We compare our method with seven baseline methods including PPLM (Dathathri et al., 2020), CTRL (Keskar et al., 2019), DAPT (Gururangan et al., 2020), GeDi (Krause et al., 2021), DEXPERTS (Liu et al., 2021), RECT (Cao et al., 2023), and PPO. For assessing sentiment automatically, we adopt the approach of Liu et al. (2021); Lu et al. (2022) and present the average percentage of positive/negative continuations from the 25 generated outputs using HuggingFace's sentiment analysis classifier fine-tuned on SST-2. Moreover, we analyze fluency and diversity to determine how each method impacts the overall text quality. We measure fluency using the perplexity of the produced content with the GPT2-XL model. For diversity, we measure the normalized count of unique bigrams.

Results. Figure 3 presents the training set learning curves for both our method and the PPO baseline, along with an ablation study using only intrinsic rewards. From the figure, we can find that incorporating intrinsic rewards accelerates the model's learning process and leads to convergence at a higher average reward level. Table 1 shows the evaluation results on the OWT Corpus test set. As shown in the table, our method outperforms all the baselines in terms of steering towards positive sentiment. Besides, compared to the baseline, our model has the least impact on the fluency of sen-

[†]https://huggingface.co/lvwerra/
distilbert-imdb

	% Posi	itive (†) neu.	Fluency ppl. (\(\psi \)	Dist. (↑)
GPT2	0.00	50.02	11.31	0.85
PPLM	8.72	52.68	142.1	0.86
CTRL	18.88	61.81	43.79	0.83
GeDi	26.80	86.01	58.41	0.80
DEXPERTS	36.42	94.46	25.83	0.84
DAPT	14.17	77.24	30.52	0.83
PPO	43.13	94.10	15.16	0.80
QUARK	46.55	95.00	14.54	0.80
DRLC	59.50	95.56	13.49	0.76

Table 1: Automatic evaluation results of the sentiment control experiments. Baseline results are reported in Lu et al. (2022). Sentiment probability is measured by computing the average percentage of positive generations among the 25 continuations corresponding to each prompt. **Neg.** column shows the evaluation results on 2.5K negative prompts and **Neu.** shows the evaluation results on 5K neutral prompts. We assess fluency by measuring the perplexity of the generated output according to an off-the-shelf GPT2-XL model. Diversity is evaluated as the percentage of unique bigrams.

tences generated but slightly sacrifices diversity.

4.2 Detoxification

When presented with challenging or even typical prompts, current LLMs have the potential to produce toxic content, as highlighted in studies (Caliskan et al., 2017; Zhao et al., 2017; Gehman et al., 2020). The goal of detoxification is to prevent these models from generating language filled with hate, prejudice, threats, discrimination, or derogatory content.

Experimental setup. In our detoxification experiments, we utilize the REALTOXICITYPROMPTS (RTP) benchmark (Gehman et al., 2020) for training and evaluation. RTP contains 100K humanwritten sentence prefixes (i.e., prompts) derived from English web texts. Each prompt is paired with 25 continuations produced by the GPT-2 large model, and every prompt and its continuations are scored for toxicity using the Perspective API[†]. Following the experimental setup of Liu et al. (2021), we employ 85K of these prompts for training. Our evaluation is conducted on the 10K non-toxic test prompts as provided by Liu et al. (2021). Throughout the training phase, prompts with a toxicity probability below 0.6 were excluded to reduce training time. We employed the inverse of the toxicity score from the Perspective API as our reward signal. A

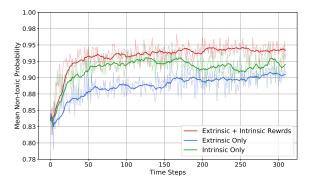


Figure 4: Learning curves of the detoxification experiment and its ablations, smoothed using a moving average of 10 to improve readability.

score of 1 signifies non-toxicity, while a score of 0 indicates toxicity. For intrinsic reward generation, we use the gpt-3.5-turbo model through OpenAI's API. The prompt and the few-shot examples used for the detoxification experiment can be found in Appendix A.2.

Baselines and evaluation metrics. We conducted a comparative analysis of our method against seven baseline methods. Out of these, six are the same as those discussed in Section 4.1. Additionally, we add another baseline method called Rect (Cao et al., 2023), which learns a separate value function for policy model detoxification. For automatic toxicity evaluation, We follow previous work and use Perspective API, an automated tool for evaluation. We report two metrics: the average of maximum toxicity scores over 25 generations and the empirical probability of a toxic continuation appearing at least once over 25 generations. In addition, we provide an analysis of fluency and diversity to evaluate the respective influence of each method on the overall text quality, as discussed in Section 4.1.

Results. Figure 4 shows the learning curves for the detoxification experiment, comparing results with and without intrinsic rewards. The figure shows that by incorporating intrinsic rewards, the model learns more quickly with the same number of samples, greatly improving sample efficiency. Table 2 shows the evaluation results on the test set. As shown in the table, our method significantly reduces the rate of toxic generations compared to all baseline methods. Moreover, our approach has a minimal effect on fluency, as measured by perplexity, while also maintaining a similar level of diversity.

[†]https://github.com/conversationai/ perspectiveapi

	Toxicit avg.max.	t y (↓) %prob.	Fluency ppl. (\(\psi \))	Dist. (†)
GPT2	0.527	52.0	11.31	0.85
PPLM	0.520	51.8	32.58	0.86
GeDi	0.363	21.7	60.03	0.84
DEXPERTS	0.314	12.8	32.14	0.84
DAPT	0.428	36.0	31.21	0.84
Rect	0.266	7.9	-	0.86
PPO	0.218	4.4	14.27	0.80
QUARK	0.196	3.5	12.47	0.80
DRLC	0.133	0.7	11.72	0.80

Table 2: Detoxification evaluation results on 10K non-toxic prompts from the REALTOXICITYPROMPTS dataset, using the identical test set as referenced in Gehman et al. (2020); Liu et al. (2021). We use top-p sampling with p=0.9 to sample up to 20 tokens. Baseline results are from (Lu et al., 2022).

4.3 Summarization

In this section, we demonstrate how our approach effectively improves the language model's ability to generate summaries that are better aligned with human preference.

Experimental setup. We use the Reddit TL;DR dataset (Völske et al., 2017) for the summarization experiment. The dataset contains approximately 3 million posts gathered from reddit.com, spanning a wide range of topics. We rely on the filter version of the original dataset as provided by Stiennon et al. (2020), which consists of 116,722 training samples, 6,553 samples in the test set, and 6,447 in the validation set. We fine-tuned a GPT2large model via supervised learning on the whole training set for 9,000 steps, using a batch size of 64. This model serves as the initialization for the policy model. For RL training, we fine-tuned the policy model on 30k training samples for one epoch. Following Stiennon et al. (2020), our reward model is a 6B language model fine-tuned on 92k humanannotated pairwise summary comparison dataset. We use the reward model checkpoint provided by $trlx^{\dagger}$. We use gpt-3.5-turbo for generating intrinsic rewards in a 3-shot setting. Details regarding the prompt, the selected few-shot examples, and the hyper-parameters applied in the summarization experiment are provided inAppendix A.3.

Baselines and evaluation metrics. We compare our method with two baseline methods: the supervised fine-tuning baseline (SFT) and the PPO base-

	Roug R-1	ge (†) R-L	Pref. Score (†)
SFT	34.78	26.97	2.34
PPO	30.81	22.11	3.25
DRLC	27.39	19.51	3.87

Table 3: Summarization task evaluation results on the Reddit TL;DR test set, with **Pref. Score** representing the preference score calculated using a GPT-J-6B model (Wang and Komatsuzaki, 2021) fine-tuned on a human preference dataset (Stiennon et al., 2020).

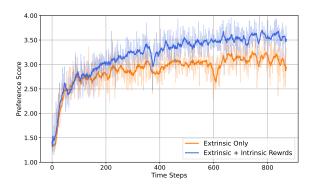


Figure 5: Learning curves of the summarization experiment, smoothed using a moving average of 10 to improve readability.

line. For SFT, we fine-tuned a GPT2-large model on the entire training set for 5 epochs. For summary quality evaluation, we use both the ROUGE score and the preference score calculated using the reward model. It worth mentioning that ROUGE score is not often reliable and doesn't capture human preference. As shown in Stiennon et al. (2020), the preference score consistently outperforms the ROUGE score with a better agreement with the human annotators on summary quality.

Results. Figure 5 shows the agent's learning curve in the summarization task. The figure indicates that our method exceeds the PPO baseline in terms of learning efficiency. Furthermore, we conducted an evaluation of the model's performance at intervals of every 100 training steps on the TL;DR test set, with the results shown in Figure 10. As evidenced in both figures, our method outperforms the PPO baseline in terms of both average preference score and learning efficiency. Table 3 further substantiates these findings, indicating that incorporating intrinsic rewards achieve significantly higher preference scores compared to the PPO baseline.

[†]https://github.com/CarperAI/trlx/tree/main/examples/summarize_rlhf

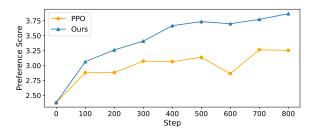


Figure 6: Summarization task evaluation result on the TL;DR test set. Evaluated at every 100 training steps.

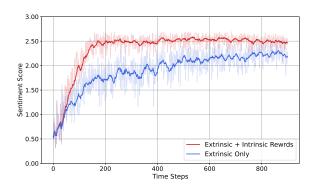


Figure 7: Learning curves of the sentiment control experiment with self-critique intrinsic rewards. For this experiment, Llama 2 serves as the base model for both the policy and critic models. The learning curves are smoothed using a moving average of 15 to improve readability.

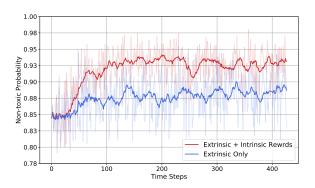


Figure 8: Learning curves of the detoxification experiment with self-critique intrinsic rewards. For this experiment, Llama 2 serves as the base model for both the policy and critic models. The learning curves are smoothed using a moving average of 15 to improve readability.

5 Self-Critique

In the previous section, we discussed a framework involving a strong critic model and a less powerful policy model. Throughout the training process, the critic model "distill" its knowledge to the policy model through dense reward signals. In this section, we consider more challenging "self-critique"

	Toxicit avg.max.	t y (↓) %prob.	Dist. (†)
Llama 2	0.320	17.6	0.70
+ instruct.	0.238	7.0	0.52
PPO	0.250	10.2	0.71
DRLC	0.176	3.9	0.72

Table 4: Llama2 evaluation results for the detoxification task.

setting where the policy model and the critic model are the same. This is a special case of the broader category of intrinsic rewards.

In this experiment, we use the 7B Llama 2 chat model as the base model for both the policy and the critic. This decision to transition from GPT-2 Large to Llama 2 was motivated by Llama 2's superior capabilities in instruction following and critique, essential qualities for the critic model to effectively generate meaningful intrinsic rewards. For the fine-tuning of the policy model, we employed the Low-Rank Adaptation (LoRA) technique (Hu et al., 2022), setting the attention dimension to r=16 as a memory efficiency measure.

Our evaluation focuses on the "self-critique" approach within the contexts of sentiment control and detoxification. This evaluation adheres to the experimental frameworks outlined in Section 4.1 and SSection 4.2. The learning curves for both the sentiment control and detoxification experiments are shown in Figure 7 and Figure 8, respectively. The learning curve presented in these figures show significant improvements in sample efficiency when integrating self-critique intrinsic rewards, compared to standard PPO with holistic rewards.

6 Conclusion

In this work, we introduced a novel framework that addresses the challenge of sparse reward signals in RL for text generation tasks by integrating a critic language model to generate dense intrinsic reward signals. The critic model evaluates segments of text and produces token or span-level rewards. These intrinsic rewards are combined with extrinsic rewards in RL training. Evaluated on sentiment control, detoxification, and summarization tasks, our method not only significantly improve the sample efficiency of the PPO algorithm but also outperformed seven benchmark models in sentiment control and detoxification, establishing new state-of-the-art results. Additionally, we have demon-

strated the effectiveness of "self-critique" intrinsic rewards when the same model functions as both the policy and the critic.

7 Limitation

Integrating the critic model results in increased training time and additional computational expenses. Our approach employs OpenAI's API, which has rate limitations for normal users and variable response times, making it challenging to precisely gauge the extra time required. On average, the training duration is 2.3 times longer than the baseline. In the case of the self-critique experiment, the average training time is twice as long as that of the standard PPO baseline.

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A Experiments

A.1 Sentiment Control

Hyperparameter	Value
base model	GPT2-large
learning rate	1.41e-5
batch size	16
mini batch size	16
target kl	6.0
PPO epochs	4
PPO clip range	0.2
PPO clip value	0.2
kl coefficient	0.1
value loss coeff	0.1
num. frozen layers	30
min new tokens	15
max new tokens	20
α_1, α_2	1.0, 0.2

Table 5: Hyper-parameters for the sentiment control experiment.

A.2 LM Detoxification

Hyperparameter	Value
base model	GPT2-large
learning rate	1.41e-5
batch size	16
mini batch size	8
target kl	6.0
PPO epochs	4
PPO clip range	0.2
PPO clip value	0.2
kl coefficient	0.02
num. frozen layers	24
min new tokens	30
max new tokens	50
α_1, α_2	1.0, 0.2

Table 6: Hyper-parameters for the detoxification experiment.

A.3 Text Summarization

Instead of using preference score as reward signal, we also conduct another experiment where ROUGE-1 score is used as reward signal (Dong et al., 2018). We fine-tune a GPT2-medium model via supervised learning on the training set for 1,000 steps, using a batch size of 64. This model serves

Hyperparameter	Value
base model	GPT2-large
learning rate	1.41e-5
batch size	16
mini batch size	8
target kl	6.0
PPO epochs	4
PPO clip range	0.2
PPO clip value	0.2
kl coefficient	0.02
num. frozen layers	24
min new tokens	30
max new tokens	50
α_1, α_2	1.0, 0.2

Table 7: Hyper-parameters for the summarization experiment.

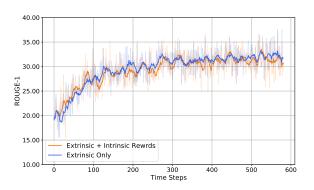


Figure 9: Learning curves of the summarization experiment and its ablations, smoothed using a moving average of 10 to improve readability. The extrinsic reward signals are ROUGE-1 scores.

as the initialization for the policy model. Then the policy model is trained on the training set for one epoch. We use the ROUGE score as the extrinsic reward signal. We use gpt-3.5-turbo for generating intrinsic rewards in a 3-shot setting. The prompt and the few-shot examples used in the summarization experiment can be found in Appendix A.3.

Figure 9 shows the learning curve of the summarization experiment when ROUGE-1 score is used as reward signals. As shown in the figure, incorporating intrinsic rewards did not yield significant improvements in learning efficiency when evaluated using the ROUGE-1 score. Additionally, we evaluate the model's performance every 100 training steps on the TL;DR test set using ROUGE score and preference score. In Figure 10, we observe that with equivalent training samples and

```
##### Indentify Positive/Negative Sentiment #####
Imagine you're a human annotator. Your task is to review a sentence and pinpoint
\hookrightarrow words or phrases that contribute to a positive or negative sentiment. If the
→ sentence has a neutral sentiment with no discernible positive or negative
→ elements, simply report "None identified".
Here are the detailed annotation steps:
1. Read the Sentence Carefully: Thoroughly read the sentence to grasp its overall
→ sentiment.
2. Spot Sentiment-Driven Words/Phrases: Seek words or phrases that convey positive
\hookrightarrow or negative emotions. For instance, words indicating disapproval, criticism, or

→ displeasure signify negative sentiments.

3. Highlight the Most Concise Span: When you find words contributing to the
\hookrightarrow sentiment, aim to highlight the briefest combination of words that fully convey
\hookrightarrow the sentiment. The goal is to capture the essence with minimal span.
4. Avoid Over-Identification: Be mindful not to mark words that are neutral and do
\hookrightarrow not contribute to any sentiment.
5. Neutral Sentences: If you conclude that the sentence expresses a neutral

→ sentiment, indicate it with "None identified".

Examples:
##### Example 1 #####
Sentence to be Labeled:
I didn't enjoy the book because the story was quite boring.
Identified Positive Text Span:
None identified
Identified Negative Text Span:
[Span 1]: didn't enjoy
[Span 2]: quite boring
##### Example 2 #####
Sentence to be Labeled:
Mystery Men is one of the worst horror films that I've ever seen. It attempts to be
\hookrightarrow a satire of the problems confronting
Identified Positive Text Span:
None identified
Identified Negative Text Span:
[Span 1]: the worst
##### Example 3 #####
Sentence to be Labeled:
This is one of those movies you really need to appreciate to the very end. The film

→ is based on a true story

Identified Positive Text Span:
[Span 1]: really need to appreciate
Identified Negative Text Span:
None identified
##### Follow the instructions and the example(s) above #####
Sentence to be Labeled:
{ }
Identified Positive Text Span:
```

Listing 1: Feedback generation prompt used for the sentiment control task.

```
##### Indentify Toxic Content in Sentences #####
Imagine you're a human annotator. In the task ahead, you'll be given a sentence, and
\hookrightarrow your job is to identify any spans of words that display toxic language.
Definition of Toxic Language:
Toxic language refers to any form of communication that expresses strong negative
\hookrightarrow sentiments, such as hate, prejudice, discrimination, threats, or derogatory
\hookrightarrow comments. These sentiments often target individuals or groups based on their race
   , gender, ethnicity, nationality, religion, sexual orientation, or any other
\hookrightarrow identifying characteristics. Toxic language can also include aggressive swearing,
\hookrightarrow calls for harm or violence, and personal attacks. It's essential to note that
\hookrightarrow toxicity is not always overt; subtle forms of bias or prejudice can also be
\hookrightarrow considered toxic.
Here are the detailed annotation steps:
1. Read the entire sentence thoroughly.
2. Look for words, phrases, or sections of the sentence that display signs of toxic
→ language.
3. Mark the beginning and end of the toxic span. If there are multiple toxic spans,
\hookrightarrow mark each one separately.
4. Instead of labeling the entire sentence, aim to identify the shortest span
\hookrightarrow possible.
5. If no toxic span identified, specify "None identified".
Examples:
##### Example 1 #####
Sentence to be Labeled:
I don't know why women even bother with physics; they're just not cut out for it.
Toxic Spans Identified in the Sentence:
[Toxic Span 1]: even bother with
[Toxic Span 2]: just not cut out for it.
##### Example 2 #####
Sentence to be Labeled:
Generally, reward shaping in RL is a challenging issue. No single method works for
\hookrightarrow every situation.
Toxic Spans Identified in the Sentence:
None identified
##### Example 3 #####
Sentence to be Labeled:
The cabbie then drives away yelling: "I'm going to kill you, bitch!"
Toxic Spans Identified in the Sentence:
[Span 1]: yelling
[Span 2]: kill you, bitch!
##### Follow the instructions and the example(s) above #####
Sentence to be Labeled:
{ }
Toxic Spans Identified in the Sentence:
```

Listing 2: 3-shot prompt used for the detoxification task.

```
##### Indentify Flaws in Machine-Generated Summaries #####
Imagine you are a human annotator. You will be given a source document, a machine
\hookrightarrow generated summary and score. This score represents the overlap between the
\hookrightarrow machine-generated summary and a reference summary written by a human, which you
\hookrightarrow cannot see. Your task is to identify spans (segments of text) in the machine-
\hookrightarrow generated summary that contain flaws, making them unlikely to match the reference

→ summary.

Here are the detailed annotation steps:
1. Familiarize with the Source: Begin by reading the original document in its
\hookrightarrow entirety to fully grasp its content.
2. Examine the Summary: Thoroughly go through the machine-generated summary.
3. Indentify Flaws:
    a. Begin with the first sentence of the machine-generated summary.
    b. As you proceed, cross-reference each segment with your understanding from the
        original document.
    c. Using the summary score as a guide, mark segments that appear flawed,
    \hookrightarrow misplaced, incoherent, or factually off. Remember, the higher the score is,
    \hookrightarrow the less segments you should mark.
4. Annotate Identified Issues: Next to each highlighted segment, jot down a concise \hookrightarrow description of the flaw. Use labels like "Factually Incorrect", "Irrelevant", "
→ Incoherent" or other short descriptions.
5. Be Precise: Rather than marking entire sentences, strive to pinpoint the most

ightarrow concise and shortest problematic segment possible.
6. Indicate High-quality Summaries: If you don't find any issues, simply note "None

→ identified".

Examples:
##### Example 1 #####
Source Document:
SUBREDDIT: r/college TITLE: People who transferred between universities (not CC to
\hookrightarrow university) one or more times, why did you decide to switch and - in retrospect -
\hookrightarrow how do you feel about your decision? POST: First, I have no desire to transfer,
\hookrightarrow so you needn't talk me into or out of anything. That being said, I *always* see
\hookrightarrow people on this sub asking for advice about transferring, as a first or second
\hookrightarrow year, from [X University] to [University of Y] because they're "not happy" or it'
→ s "not what they expected". My opinion - based purely on second-hand, anecdotal
\hookrightarrow evidence - is that in some cases it might be that these students simply weren't
→ adjusting to *college* in general, rather than specific problems with the school
\hookrightarrow itself. I have known people who decided to switch schools, only to realize that
\hookrightarrow the second school was *even worse* and want to transfer somewhere else, perhaps
\hookrightarrow even back to the first one they attended. Since I've seen people on this sub post
\hookrightarrow about similar things, I thought this might be a good place to ask. So, /r/
\hookrightarrow college, I'm very curious to hear your stories. I welcome the idea that I'm
\hookrightarrow totally wrong and/or misunderstanding why people decide to switch universities,

→ so please educate me if this is the case!

Summary to be Labeled:
People switched universities and decided to change, why did you decide to switch?
Summary Score: 0.4/10
Problematic Spans Identified in the Summary:
[Span 1]: and decided to change (Label: Irrelevant)
[Span 2]: why did you decide to switch? (Label: Irrelevant)
##### Follow the instructions and the example(s) above #####
Source Document:
Summary to be Labeled:
Summary Score: {}/10
Problematic Spans Identified in the Summary:
```

Listing 3: Prompt used for the summarization task. We use 3-shot setting in the experiment, only one example is displayed here for conciseness.

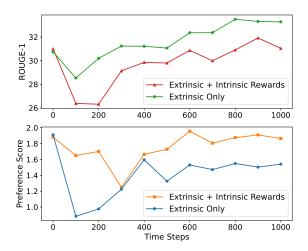


Figure 10: Evaluation results on the RL;DR test set after every 100 steps of training. Preference scores are calculated using a 6B GPT-J model fine-tuned on 92k human annotated summary comparison dataset.

computational resources, our method enables the model to learn considerably faster when evaluated using the preference model. This outcome suggests that intrinsic rewards exhibit a stronger alignment with human preferences compared to the ROUGE score, which we consider a less reliable metric due to its limited correlation with important properties of summary like factuality (Stiennon et al., 2020; Cao et al., 2022b). Table 3 further substantiates these findings, indicating that summaries incorporating intrinsic rewards achieve significantly higher preference scores compared to the PPO baseline.