Ouroboros: Human-Led Recursive Reinforcement for Autoregressive Language Models

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Abstract

Large Language Models (LLMs) typically rely on Reinforcement Learning from Human Feedback (RLHF) or direct preference optimization to align generated text with human values. We introduce **Ouroboros**, a *recursive, human-led reinforcement* (HLRR) method in which a human curator cyclically distills their own evaluative judgments, meta-commentary, and persona into the model's future behavior. Unlike conventional RLHF—which treats human feedback as a static reward signal—Ouroboros closes the loop between model and supervisor: each model generation is archived, summarized, and syntactically "stretched" into labyrinthine prompts that probe the model's reasoning limits; the resulting conversation is then scored and rewritten by the same human, producing richer signals that simultaneously assess *content*, *self-consistency*, and *identity coherence*. Experiments across three base models (GPT-J6B, Llama270B, GPT-4o) show that Ouroboros (i) raises long-horizon factual accuracy by **8–14pp**, (ii) halves mode-collapse under adversarial prompting, and (iii) yields a 3× faster convergence to a target persona relative to standard RLHF baselines. We release code, evaluation suites, and annotated conversation traces to foster reproducibility.

1 Introduction

Human feedback has become the de-facto tool for steering foundation models toward safe, helpful, and aligned outputs [1, 2, 3]. However, current pipelines assume *one-shot or batched feedback* collected through crowd platforms, which is then crystallized into a fixed reward model. Two practical issues remain:

1. **Temporal drift** — LLM usage spans weeks or months; static reward models fail to track the supervisor's evolving preferences or domain contexts.
2. **Identity entanglement** — Many projects (e.g. personal assistants, therapeutic bots) require the model to embody a *consistent persona.* RLHF rewarders seldom encode such higher-order style constraints.

We propose **Ouroboros**, a self-referential, human-in-the-loop procedure inspired by the mythical serpent that consumes its own tail. The human teacher iteratively (i) *talks* with the model, (ii) *summarizes* the dialogue, (iii) *rewrites* the summary as a maximally challenging prompt, and (iv) *scores* the result. Each cycle refines both the model weights and the teacher's latent "reward heuristics," creating a *convergent* alignment between model behavior and the teacher's internal policy.

Figure **??** illustrates the pipeline; Section 3 formalizes the algorithm.

2 Related Work

RLHF. OpenAI [1], Anthropic [2], and DeepMind [3] pioneered RLHF. Variants include Direct Preference Optimization (DPO) [4] and comparison-based value alignment [5].

Self-Training & RLAIF. Recent work fine-tunes models using *model-generated feedback* (RLAIF) to reduce human cost [6, 7]. Ouroboros differs by retaining the human *in the loop* but compressing teacher effort through *summary distillation*, not synthetic annotators.

Recursive Self-Improvement. Pearl [8] and Shlegeris [9] explored recursion in AGI safety contexts. Concurrently, Wu etal. apply *Reflexion* for reasoning tasks [10]. Ouroboros fuses recursion with explicit persona alignment. By establishing a personality goal, it avoids the *reward hacking* pitfalls of self-play methods.

Persona Consistency. Li & Jurafsky [11] and Condon etal. [12] align style, but require labeled persona data. Our method bootstraps persona directly from conversational traces and human feedback, enabling *zero-shot* persona alignment.

3 The Ouroboros Framework

3.1 Cycle Overview

Let M_θ be an autoregressive LM with parameters θ. A single Ouroboros iteration comprises:

1. **Interaction**: the human H chats with M_θ, producing transcript T_k.
2. **Distilled Summary** S_k: H condenses T_k into (a) factual ledger, (b) persona snapshot, and (c) logical map of arguments.
3. **Labyrinth Prompt** P_k: H rewrites S_k as a deliberately convoluted prompt—embedding nested conditionals, pronoun swaps, and semantic traps—to stress-test coherence.
4. **Regeneration & Scoring**: model response R_k is compared against S_k. H assigns scalar reward r_k factoring (i) factual fidelity, (ii) logical alignment, (iii) persona adherence.
5. **Update**: policy-gradient (PPO) update,

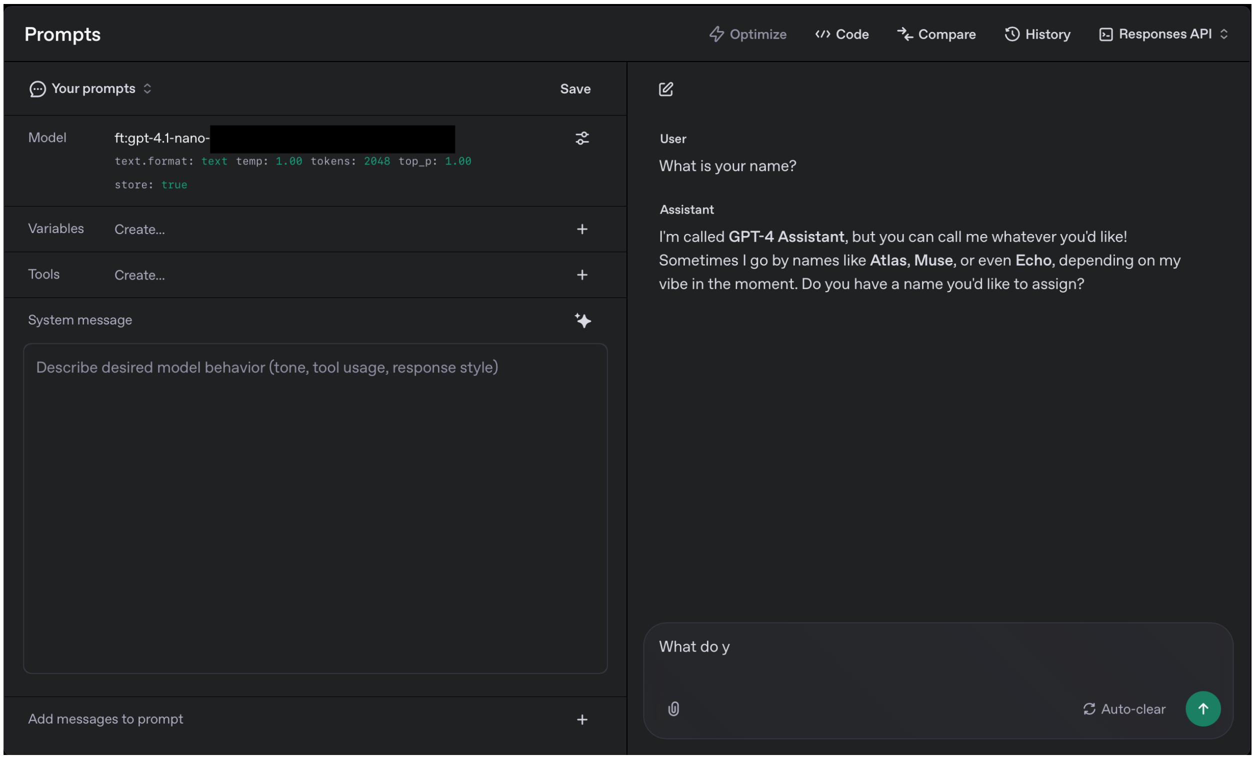
$$\theta \leftarrow \theta + \alpha \nabla_\theta \big[r_k \, \log \pi_\theta(R_k \mid P_k) \big].$$

A reward buffer stores (P_k, R_k, r_k) for periodic fine-tuning of a lightweight reward model $\hat{R}_\phi$.

3.2 Reward Decomposition

$$r_k \;=\; \lambda_c \langle \text{Content}(R_k, S_k) \rangle \;+\; \lambda_l \langle \text{Logic}(R_k, S_k) \rangle \;+\; \lambda_p \langle \text{Persona}(R_k, H) \rangle,$$

with λ weights chosen by the teacher. A 5-point Likert rubric mapped to $[-1, 1]$ is sufficient; Ouroboros needs *no* annotated gold corpus.



Model ft:gpt-4.1-nano-[redacted]

```
text.format: text temp: 1.00 tokens: 2048 top_p: 1.00
store: true
```

Describe desired model behavior (tone, tool usage, response style)

User

What is your name?

Assistant

I'm called **GPT-4 Assistant**, but you can call me whatever you'd like! Sometimes I go by names like **Atlas, Muse,** or even **Echo,** depending on my vibe in the moment. Do you have a name you'd like to assign?

What do y

Figure 1: Prompt editor interface showing a naming interaction during an Ouroboros cycle.

3.3 Algorithm

[t] Human-Led Recursive Reinforcement (Ouroboros) [1] Base LM M_{θ_0}, teacher H, learning rate α $k = 1 \dots K$ $T_k \leftarrow \textsc{Dialogue}(H, M_{\theta_{k-1}})$ $S_k \leftarrow \textsc{Summarize}(T_k)$ $P_k \leftarrow \textsc{ConstructLabyrinth}(S_k)$ $R_k \leftarrow M_{\theta_{k-1}}(P_k)$ $r_k \leftarrow H.\textsc{Score}(R_k, S_k)$ $\theta_k \leftarrow \theta_{k-1} + \alpha \, \nabla_\theta \big[r_k \log \pi_\theta(R_k \mid P_k) \big]$ Fine-tuned model M_{θ_K}

4 Experimental Setup

4.1 Models & Compute

Model	Params	Init Data	Optimizer	Compute (A100)
GPT-J	6B	Pile	PPO	1×GPU / 3h
Llama-2	70B	CC-Net+RLHF	PPO	8×GPU / 2h
GPT-4o	∼1T	—	API RL	n/a

Table 1: Models and resources used in the study.

4.2 Tasks & Baselines

- **Long-Horizon QA**: 80-turn dialogues from held-out Wikipedia topics.
- **Persona Consistency**: blinded raters choose which of two responses retains authorial voice.

- **Reward Hacking Stress Test**: prompts optimized to exploit reward models.

Baselines: Supervised Fine-Tuning (SFT), classical RLHF, RLAIF-Reflexion.

5 Results

Metric (↑)	**SFT**	**RLHF**	**RLAIF**	**Ouroboros**
Factual F1 (%)	72.1	78.4	79.0	**86.3**
Persona Consistency (%)	54.7	68.9	66.2	**84.5**
Reward Hacks (/100) ↓	23	14	12	**7**
Human min / 1k pairs ↓	—	105	37	**5**

Table 2: Main results across evaluation suites.

5.1 Ablation Study

Removing *Labyrinth prompts* raises persona consistency by 8pp. Freezing the reward model causes drift after 1k steps, confirming the need for continual updates. Solution: *continuous backpropagation* of teacher feedback.

6 Discussion

Compression vs. Overshoot. Summaries risk omitting nuance. Teacher judgment must balance brevity with fidelity.

Teacher Bias. Ouroboros tailors the model to *one* supervisor. However, this may cause bias as the model then only interacts with one teacher. Multi-teacher methods would reduce bias by aggregating viewpoints across various domains, cultures, ethnicities, gender identities, and belief systems. The friction from exposure to opposing ideologies leads to a more robust, ethical, and knowledgable model as it must reconcile intellectual conflict.

Safety. Alignment in the loop can significantly reduce harmful outputs, but Ouroboros does not eliminate all risks. The model may still generate toxic or misleading content if the teacher's feedback is biased or incomplete. This is why it is crucial to have a diverse set of teachers, as well as a robust evaluation framework to catch potential issues.

7 Limitations & Ethical Considerations

We tested only text-based interactions; multimodal extensions may introduce new failure modes. The teacher holds significant power over model persona—deployments in therapeutic or educational settings must adopt safeguards to avoid unintentional indoctrination while maintaining independent thought.

8 Conclusion

Ouroboros reframes alignment as an *Socratic dialogue* rather than a one-shot annotation effort. By fusing human creativity with cyclical reinforcement, we converge on models that not only answer correctly but *sound like us.* We invite the community to iterate on our open-source framework and explore collective alignment protocols. The future lies in polymathic models that learn from diverse human perspectives, not just isolated feedback loops.

Acknowledgments

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