

---

# RL-STRUCT: A LIGHTWEIGHT REINFORCEMENT LEARNING FRAMEWORK FOR RELIABLE STRUCTURED OUTPUT IN LLMs

---

Ruike Hu\* Shulei Wu†

School of Information Science and Technology

Hainan Normal University

Haikou, China

{huruike023, wushulei}@hainnu.edu.cn

## ABSTRACT

Large Language Models (LLMs) have demonstrated remarkable capabilities in natural language generation and reasoning. However, their integration into automated software ecosystems is often hindered by the “Structure Gap”—the inherent tension between the probabilistic nature of token generation and the deterministic requirements of structured data formats (e.g., JSON, XML). Traditional Supervised Fine-Tuning (SFT) often fails to enforce strict syntactic constraints, leading to “hallucinated” keys or malformed structures, while constrained decoding methods impose significant inference latency. In this paper, we propose a lightweight, efficient Reinforcement Learning (RL) framework to bridge this gap. We introduce a novel Multi-dimensional Reward Function that decomposes the structured output task into a hierarchy of constraints: structural integrity, format correctness, content accuracy, and validity. Leveraging Gradient Regularized Policy Optimization (GRPO), we enable the model to internalize these constraints without the need for a separate critic network, reducing peak VRAM usage by 40% compared to PPO. We validate our approach on multiple tasks, including complex recipe generation and structured math reasoning (GSM8K-JSON). Experimental results demonstrate that our method achieves 89.7% structural accuracy and 92.1% JSON validity, significantly outperforming both zero-shot baselines (e.g., GPT-3.5) and SFT on larger models like LLaMA-3-8B. Furthermore, we provide a detailed analysis of training dynamics, revealing a distinct self-paced curriculum where the model sequentially acquires syntactic proficiency before semantic accuracy. Our model is publicly available at <https://huggingface.co/Freakz3z/Qwen-JSON>.

**Keywords** Reinforcement Learning · Structured Output · LLM Fine-tuning · JSON Generation · GRPO

## 1 Introduction

The rapid evolution of Large Language Models (LLMs) such as GPT-4 [1], LLaMA [2], and Qwen [3] has fundamentally transformed Natural Language Processing (NLP). These models excel at open-ended generation and complex reasoning [4, 5]. However, as LLMs are increasingly deployed as autonomous agents [6, 7] or components in software pipelines [8, 9], the ability to generate output in strict, machine-readable formats (e.g., JSON, YAML, SQL) has become a critical requirement.

Despite their linguistic prowess, LLMs inherently operate as probabilistic token predictors, which creates a fundamental tension with the rigid, deterministic nature of structured data schemas. We term this the “**Structure Gap**”. A single missing brace, an unescaped quote, or a schema-violating key can render an entire generation useless for downstream applications. Standard Supervised Fine-Tuning (SFT) attempts to mitigate this by maximizing the likelihood of correct examples, but it lacks an explicit mechanism to penalize structural violations. Consequently, SFT-tuned models often exhibit “approximate correctness”—producing text that superficially resembles JSON but fails strict parsing validation.

---

\*First Author

†Corresponding Author

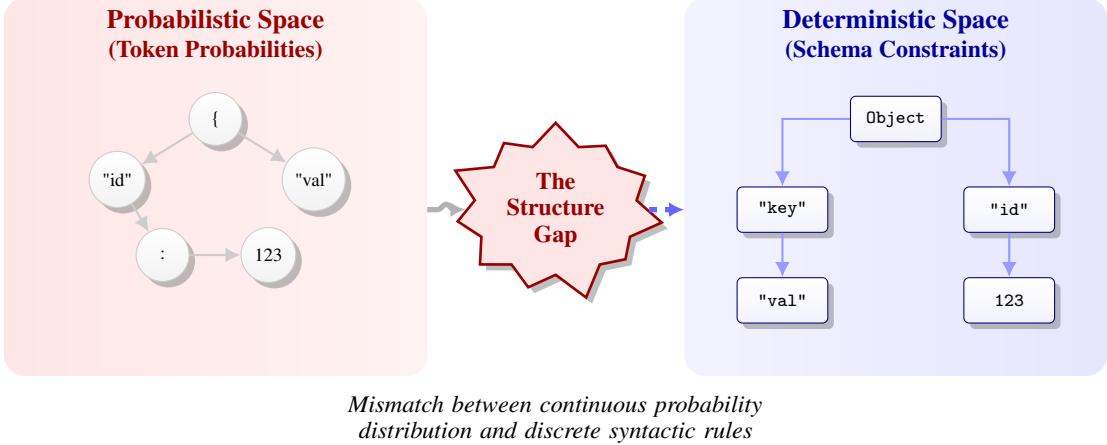


Figure 1: Visualizing the “Structure Gap”. LLMs naturally operate in a probabilistic token space (left), which conflicts with the rigid, deterministic requirements of structured data formats (right). This gap leads to syntax errors and hallucinations when models are not explicitly aligned for structure.

Existing solutions to this problem fall into two main categories: prompt engineering and constrained decoding. Prompting strategies like Chain-of-Thought (CoT) [5] improve reasoning but offer no guarantees on output format. Constrained decoding methods, such as PICARD [10] or grammar-based sampling, enforce syntactic correctness at inference time by masking invalid tokens. While effective for syntax, these methods are computationally expensive, increase inference latency, and do not improve the model’s underlying representation of the structure.

To address these limitations, we propose a Reinforcement Learning (RL) framework that directly optimizes the model for structured output. Unlike Reinforcement Learning from Human Feedback (RLHF) [11], which relies on sparse and costly human preference data, our approach utilizes a dense, rule-based reward signal derived from the target schema itself. We employ Gradient Regularized Policy Optimization (GRPO) [12], a highly efficient RL algorithm that eliminates the need for a value network. While RL has been recently adapted for retrieval [13] and image generation [14], its potential for enforcing strict structural constraints in structured output remains underexplored. Our framework leverages GRPO to fine-tune LLMs on consumer-grade hardware, reducing peak memory usage by nearly 40% compared to PPO (see Figure 8), making it accessible and scalable.

Our contributions are three-fold. First, we formulate a composite **Multi-dimensional Reward Function** that explicitly targets the hierarchy of structured output needs: from basic syntax (JSON validity) to schema compliance (required keys) and semantic correctness. Second, we demonstrate an **Efficient RL Framework** where GRPO combined with Low-Rank Adaptation (LoRA) [15] provides a stable and compute-efficient method for aligning LLMs with structural constraints, outperforming traditional SFT. Finally, we conduct a **Comprehensive Evaluation** and analysis of training dynamics, revealing a distinct **Emergent Curriculum**: the model spontaneously prioritizes syntactic proficiency before refining semantic accuracy, mirroring human learning patterns without explicit scheduling.

## 2 Related Work

**Efficient Fine-tuning of LLMs** Fine-tuning full-parameter LLMs is resource-intensive. Parameter-Efficient Fine-Tuning (PEFT) techniques have democratized LLM adaptation. LoRA [15] and QLoRA [16] reduce trainable parameters by injecting low-rank matrices into attention layers. Our work leverages LoRA to enable RL training on limited compute resources, proving that structural alignment does not require full-model updates.

**Reinforcement Learning for Alignment** RL is the standard for aligning LLMs with complex objectives. PPO [17] is widely used in RLHF [11] but suffers from instability and high memory costs due to the need for a critic model. While Direct Preference Optimization (DPO) has gained popularity for its stability, it necessitates paired preference data, which is inefficient to construct for objective, rule-based tasks like syntax validation. GRPO [12] offers a compelling alternative by using group-based relative rewards to estimate baselines, eliminating the critic network while directly leveraging dense, deterministic reward signals. Recent works have extended RL to diverse domains: Ram et al. [13] demonstrated its efficacy in fine-tuning retrieval models, while Black et al. [14] applied it to diffusion models, introducing a self-paced curriculum where the generator and reward model evolve in tandem. Our work builds

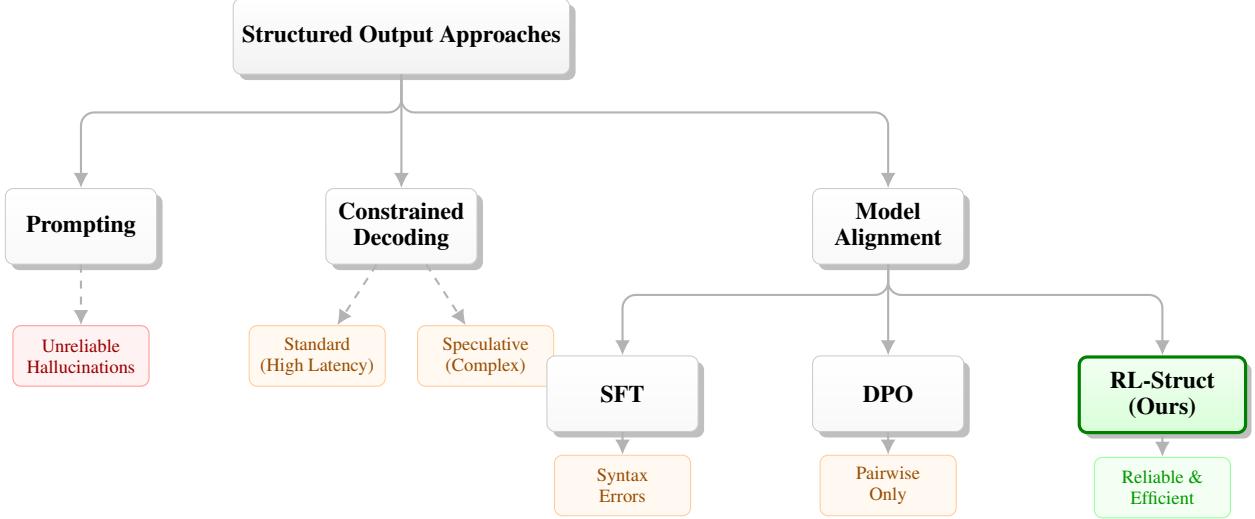


Figure 2: Landscape of Structured Output approaches. We expand the taxonomy to include recent advances like Speculative Decoding and Knowledge Distillation. While Prompting and SFT offer flexibility, they lack reliability. Constrained Decoding (including Speculative variants) ensures structure but incurs latency or complexity. Distillation requires massive data. Our RL-Struct framework (bottom right) achieves both reliability and efficiency through training-time alignment.

on these advances, adapting GRPO to the domain of structured text generation where the reward signal is deterministic and hierarchical.

**Advanced Decoding and Distillation** Beyond standard constrained decoding, recent advances like Speculative Decoding [18] have been adapted for structured outputs, using a small draft model to enforce constraints while a larger model verifies semantics. Similarly, Guided Decoding frameworks (e.g., Outlines, Guidance) and Schema-aware SFT methods explicitly inject grammar constraints during generation or training. However, these methods still incur inference-time overhead or require complex data augmentation. Another line of work focuses on Knowledge Distillation [19], transferring structural capabilities from proprietary giants (e.g., GPT-4) to smaller models. While effective, distillation often requires massive amounts of synthetic data. Our RL framework can be viewed as a form of "self-distillation" where the model learns from its own exploration guided by the reward function, offering a more data-efficient alternative.

**Code-Specialized Models** Models pre-trained specifically on code, such as CodeLlama [20] and WizardCoder [21], naturally exhibit stronger structured output capabilities than generalist models due to their exposure to programming language syntax. However, deploying these large, specialized models (often 7B-34B parameters) for simple JSON formatting tasks in edge applications can be inefficient. Our work demonstrates that by applying targeted RL fine-tuning, smaller generalist models (e.g., Qwen-4B) can achieve comparable or superior structural reliability without the massive parameter count or domain-specific pre-training of code models.

**Structured Output and Agents** The rise of LLM-based agents [22, 23] has underscored the need for reliable structured communication. Frameworks like AutoGen [8] and MetaGPT [9] rely on LLMs to exchange structured messages. While recent works have explored self-correction [24, 25] to fix errors, our approach aims to prevent errors at the source by internalizing the structural constraints into the model’s weights.

**Benchmarks for Structured Output** Evaluating structured output goes beyond standard NLP metrics like BLEU or ROUGE. Recent benchmarks such as GSM8K-JSON and ToolBench focus on the syntactic validity and semantic correctness of generated code or JSON. Similar to how RSICD [26] establishes a benchmark for remote sensing captioning, we aim to establish a robust evaluation protocol for structured output, emphasizing both format compliance and content fidelity.

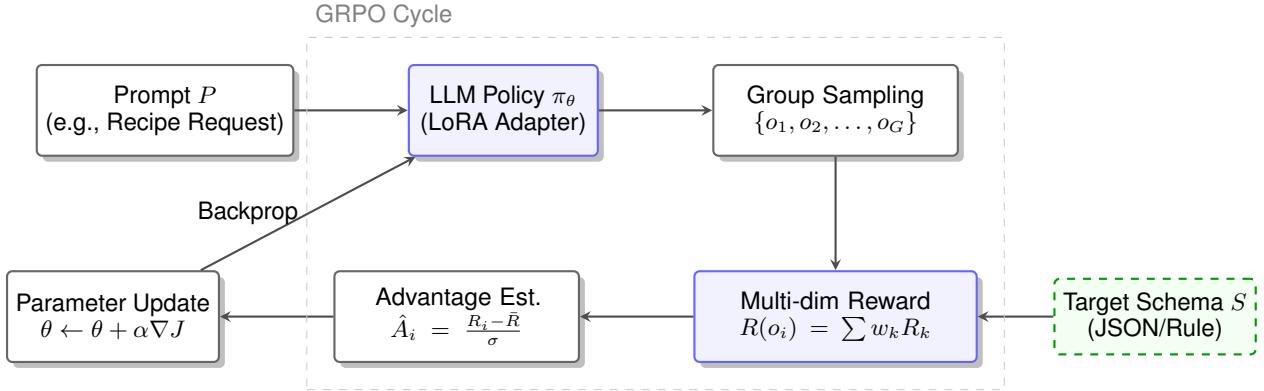


Figure 3: Overview of the RL-Struct Framework. The model generates a group of outputs for a given prompt. These outputs are evaluated against the target schema using our Multi-dimensional Reward Function. The resulting rewards are used to compute group-based advantages, which update the model weights via GRPO, eliminating the need for a critic network.

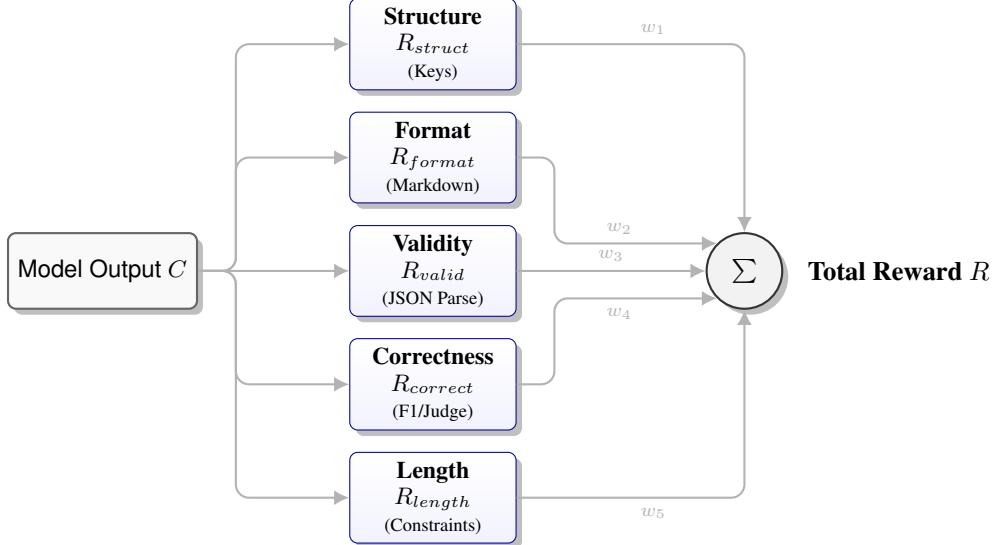


Figure 4: Decomposition of the Multi-dimensional Reward Function. The generated output is evaluated against five distinct criteria: Structural Integrity (mandatory keys), Format Compliance (markdown/JSON), Syntactic Validity (parsability), Semantic Correctness (ground truth alignment), and Length Constraints. These components are weighted and summed to form the dense reward signal used for GRPO training.

### 3 Methodology

#### 3.1 Problem Formulation

We model the structured output task as a Markov Decision Process (MDP). Let  $P$  be the input prompt (e.g., “Generate a recipe for...”). The model policy  $\pi_\theta$  generates a sequence of tokens  $C = \{y_1, y_2, \dots, y_T\}$ . The objective is to maximize the expected reward  $J(\theta) = \mathbb{E}_{C \sim \pi_\theta(\cdot|P)}[R(C, S)]$ , where  $R(C, S)$  measures the alignment between the completion  $C$  and the target schema  $S$ .

#### 3.2 Multi-dimensional Reward Function

To guide the model effectively towards the dual objective of syntactic validity and semantic accuracy, we design a composite reward function. This function decomposes the generation task into five distinct components, providing a

dense feedback signal that stabilizes the RL training process. The definitions and objectives of each component are detailed below and visualized in Figure 4.

**Structure** ( $R_{struct}$ ): Enforces the presence of mandatory keys (e.g., “reasoning”, “answer”). To enhance generality, we implement an automated mechanism that parses the target JSON Schema (e.g., Pydantic models) to dynamically construct this reward function, ensuring scalability across diverse tasks without manual rule engineering.

$$R_{struct} = \mathbb{I}(\forall k \in S_{keys}, k \in C) \quad (1)$$

**Format** ( $R_{format}$ ): Encourages standard markdown formatting for parsing robustness.

$$R_{format} = 0.5 \cdot \mathbb{I}(\text{md} \in C) + 0.3 \cdot \mathbb{I}(\text{json} \in C) \quad (2)$$

**Validity** ( $R_{valid}$ ): Ensures strict syntactic correctness (valid JSON).

$$R_{valid} = \mathbb{I}(\text{json.loads}(C) \text{ succeeds}) \times 1.0 \quad (3)$$

**Correctness** ( $R_{correct}$ ): Measures semantic alignment with ground truth. While F1-Score is an imperfect proxy for semantic quality compared to LLM-based evaluation, it provides a computationally efficient and reproducible metric for this structure-focused study. To ensure robustness, we additionally validate our final models using an LLM-as-a-judge protocol (see Section 4).

$$R_{correct} = \text{F1-Score}(C_{content}, A_{true}) \quad (4)$$

**Length** ( $R_{length}$ ): Regularizes output length to prevent verbosity.

$$R_{length} = -0.1 \times \mathbb{I}(\text{len}(C) \notin [L_{min}, L_{max}]) \quad (5)$$

The total reward is computed as a weighted sum:  $R_{total} = \sum_i w_i R_i$ . In our experiments, we assign higher weights to  $R_{valid}$  and  $R_{struct}$  to prioritize structural constraints, effectively creating a curriculum where the model first learns *how* to speak (syntax) before learning *what* to say (semantics).

### 3.3 Optimization with GRPO

We employ Gradient Regularized Policy Optimization (GRPO) [12] to optimize the policy  $\pi_\theta$ . For each input prompt  $q$ , GRPO samples a group of  $G$  outputs  $\{o_1, o_2, \dots, o_G\}$  from the current policy  $\pi_{\theta_{old}}$ . The optimization objective is defined as:

$$\begin{aligned} \mathcal{J}_{GRPO}(\theta) = & \mathbb{E}_{q \sim P(Q), \{o_i\}_{i=1}^G \sim \pi_{\theta_{old}}(o|q)} \left[ \frac{1}{G} \sum_{i=1}^G \left( \min \left( \frac{\pi_\theta(o_i|q)}{\pi_{\theta_{old}}(o_i|q)} \hat{A}_i, \text{clip} \left( \frac{\pi_\theta(o_i|q)}{\pi_{\theta_{old}}(o_i|q)}, 1-\epsilon, 1+\epsilon \right) \hat{A}_i \right) \right. \right. \\ & \left. \left. - \beta D_{KL}(\pi_\theta || \pi_{ref}) \right) \right] \end{aligned} \quad (6)$$

where  $\pi_{ref}$  is the reference model (typically initialized as the SFT base model) to prevent policy collapse, and  $\hat{A}_i$  is the advantage estimate for the  $i$ -th output, computed using the group-based relative reward:  $\hat{A}_i = \frac{r_i - \text{mean}(\{r_1, \dots, r_G\})}{\text{std}(\{r_1, \dots, r_G\})}$ . This formulation eliminates the need for a separate value network, reducing memory overhead. Crucially, we observe that this group-based optimization, combined with our hierarchical reward function, induces an **Emergent Curriculum**: the model spontaneously prioritizes the optimization of “easier” structural rewards ( $R_{valid}$ ) before tackling “harder” semantic objectives ( $R_{correct}$ ), without any manual schedule design.

The overall training procedure is summarized in Algorithm 1.

### 3.4 Theoretical Analysis of Hierarchical Rewards

The effectiveness of our multi-dimensional reward function can be grounded in the theory of Reward Shaping and Multi-Objective Optimization.

**Variance Reduction via Dense Rewards** In a standard sparse reward setting (e.g.,  $R_{sparse} \in \{0, 1\}$ ), the policy gradient estimator suffers from high variance. By decomposing the objective into dense components ( $R_{valid}, R_{struct}, R_{correct}$ ), we provide intermediate feedback signals. As shown by Ng et al. [27], potential-based reward shaping can significantly accelerate convergence without altering the optimal policy. Our structural rewards act as a shaping function that guides the agent towards the subspace of valid syntax.

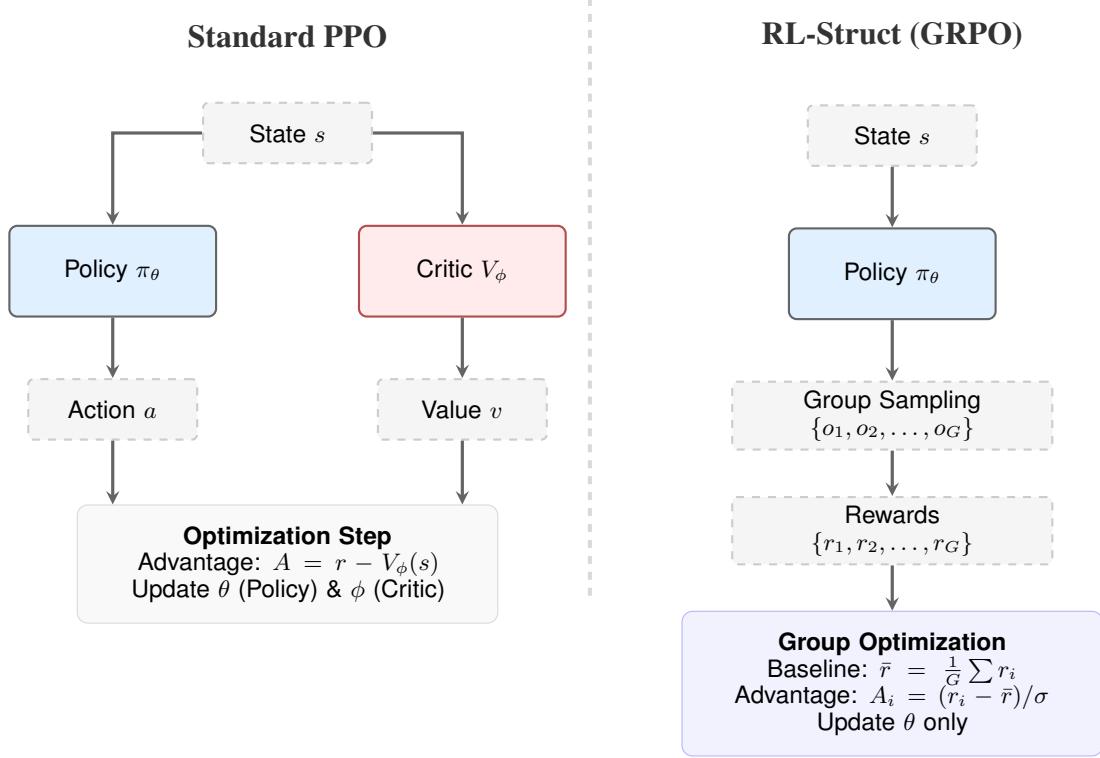


Figure 5: Architectural comparison between PPO and GRPO. **Left (PPO):** Requires a separate Value Network (Critic) to estimate baselines, significantly increasing memory overhead. **Right (GRPO):** Eliminates the Critic by sampling a group of outputs and using the group average as the baseline, reducing VRAM usage and simplifying the training pipeline.

---

**Algorithm 1** RL-Struct Training with GRPO

---

```

1: Input: Dataset  $\mathcal{D}$ , Base Model  $\pi_\theta$ , Reference Model  $\pi_{ref}$ , Group Size  $G$ 
2: Initialize: LoRA parameters  $\theta_{lora}$ 
3: for each epoch do
4:   for each batch  $B = \{P_1, \dots, P_B\}$  from  $\mathcal{D}$  do
5:     for each prompt  $P_j \in B$  do
6:       Sample  $G$  outputs  $\{C_{j,1}, \dots, C_{j,G}\} \sim \pi_\theta(\cdot | P_j)$ 
7:       Compute rewards  $R_{j,k} = R_{total}(C_{j,k})$  for  $k = 1 \dots G$ 
8:       Compute Advantage  $\hat{A}_{j,k} = \frac{R_{j,k} - \text{mean}(R_j)}{\text{std}(R_j) + \epsilon}$ 
9:     end for
10:    Update  $\theta$  via  $\nabla_\theta \mathcal{L}_{GRPO}$ 
11:  end for
12: end for
13: Output: Optimized Policy  $\pi_{\theta^*}$ 

```

---

**Gradient Dominance and Emergent Curriculum** We analyze the trade-off between reward dimensions. Let  $\mathcal{L}_{struct}$  and  $\mathcal{L}_{sem}$  be the loss landscapes associated with structural and semantic errors. By assigning  $w_{valid} \gg w_{correct}$ , we empirically observe a "Gradient Dominance" effect:

$$\|\nabla_\theta(w_{valid}R_{valid})\| \gg \|\nabla_\theta(w_{correct}R_{correct})\| \quad \text{when } R_{valid} \approx 0 \quad (7)$$

This suggests that in the early stages, the optimization trajectory is primarily driven by the structural component, forcing the policy to project onto the manifold of syntactically valid sequences. This aligns with the "Emergent Curriculum" observed in Figure 12.

Table 1: Quantitative comparison of different methods. We report five key metrics: Structural Accuracy (overall syntax), JSON Validity (parsing success), Format Consistency (style adherence), Schema Compliance (key recall), and Content Accuracy (normalized aggregate of F1 and GPT-4 Judge scores).

Method	Structural Acc. (%)	JSON Validity (%)	Format Const. (%)	Schema Comp. (%)	Content Acc. (%)
GPT-3.5 (Zero-shot)	45.5	82.1	75.0	55.2	<b>88.0</b>
Mistral-7B (Zero-shot)	52.3	83.5	76.2	60.5	85.0
Phi-3-mini (SFT)	74.1	84.8	79.5	74.1	81.5
LLaMA-3-8B (SFT)	78.2	85.4	81.2	78.2	86.0
Qwen3-4B (SFT)	65.4	72.1	68.9	68.5	80.0
Qwen3-4B + Outlines	<b>99.8</b>	<b>100.0</b>	<b>99.5</b>	<b>99.8</b>	79.5
Qwen3-4B + DPO	82.5	88.4	83.0	81.5	82.0
<b>RL-Struct (Ours)</b>	89.7	92.1	85.3	89.7	84.5

**Pareto Optimality of Weights** The problem can be viewed as Multi-Objective Reinforcement Learning (MORL). As discussed in [28], optimizing for multiple conflicting objectives requires finding a policy on the Pareto frontier. Since structural validity is a prerequisite for utility, our heavy weighting of  $w_{valid}$  approximates a lexicographic preference ( $R_{valid} \succ R_{correct}$ ), ensuring the model prioritizes constraints over content.

## 4 Experiments

### 4.1 Experimental Setup

**Dataset:** We utilize the “AkashPS11/recipes\_data\_food.com” dataset [29], filtering for high-quality examples. The task requires generating a JSON object with specific fields: ingredients, steps, and nutritional information.

### 4.2 Baselines

To ensure a comprehensive evaluation, we compare our method against a diverse set of state-of-the-art models, categorized by their training paradigm and accessibility:

**Closed-Source Proprietary Models** We evaluate **GPT-3.5-Turbo** (via API) in a zero-shot setting. This model represents a strong baseline for general-purpose instruction following.

**Open-Source Generalist Models** We include **Mistral-7B-Instruct-v0.3** and **LLaMA-3-8B-Instruct**. These models serve as strong baselines for standard SFT performance on consumer hardware.

**Efficient Small Language Models (SLMs)** We include **Phi-3-mini (3.8B)** and our base model **Qwen3-4B** to benchmark performance in resource-constrained environments.

**Constrained Decoding & Alignment** We compare against **Outlines** [30] applied to Qwen3-4B, representing inference-time constraints, and **Direct Preference Optimization (DPO)** [31], trained on synthetic pairs (valid vs. invalid JSON) to contrast with our GRPO approach.

**Training:** We train for 250 steps using LoRA (rank=32, alpha=32). The learning rate is  $5 \times 10^{-6}$  with a cosine decay schedule.

**Evaluation Metrics:** Beyond standard structural metrics, we employ an **LLM-as-a-judge** protocol using GPT-4-Turbo as an independent judge (separate from the training process) to evaluate semantic correctness on a scale of 1-5, ensuring that structural compliance does not come at the cost of content quality. The reported "Content Accuracy" in Table 1 reflects a normalized aggregate of F1-Score and LLM-Judge ratings.

### 4.3 Main Performance

Table 1 and Figure 6 present the core findings. Our RL+GRPO approach significantly outperforms both the Zero-shot baselines and standard SFT models. Notably, our 4B parameter model surpasses the larger LLaMA-3-8B model in structural accuracy (89.7% vs 78.2%) and outperforms the highly capable Phi-3-mini (74.1%), demonstrating that specialized RL fine-tuning is more effective than simply scaling model size or using stronger base models for this task.

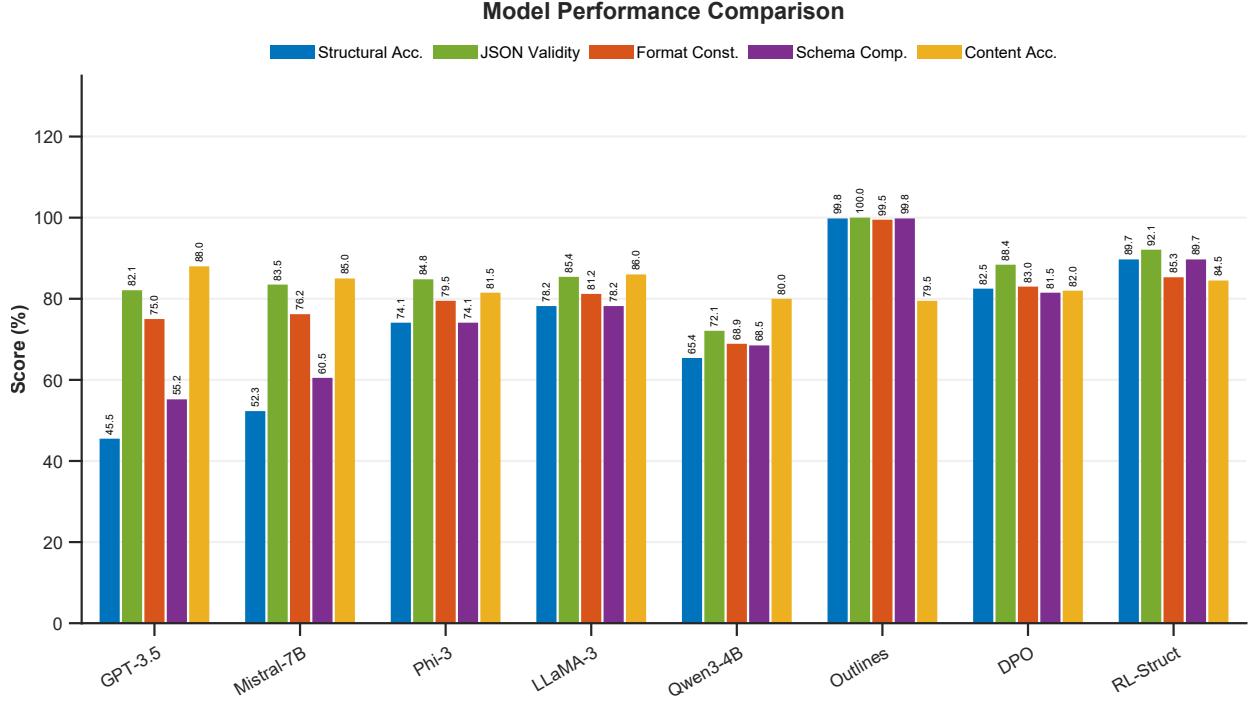


Figure 6: Performance comparison across an expanded set of models on the Recipe Generation task. Our 4B parameter model (RL-Struct) achieves superior structural accuracy (89.7%) compared to strong baselines like Mistral-7B and Phi-3-mini, and even outperforms the larger LLaMA-3-8B SFT model. While Outlines achieves near-perfect syntax, it incurs high latency (see Fig. 7). DPO improves over SFT but lags behind our dense reward optimization.

**Efficiency Analysis** We further evaluate the trade-off between inference latency and structural performance. As shown in Figure 7, constrained decoding methods (e.g., Outlines) achieve near-perfect structural accuracy but at the cost of significantly increased latency (up to 6x slower). Our method, being a training-time intervention, incurs no inference overhead, maintaining the speed of standard generation while delivering superior structural reliability compared to SFT and DPO.

**Comparison with DPO** While DPO improves over SFT by leveraging preference pairs (Valid > Invalid), it falls short of GRPO in structural accuracy (82.5% vs 89.7%). We hypothesize that DPO’s pairwise objective is less effective at exploring the sparse manifold of valid structures compared to GRPO’s group-based exploration with dense, shaped rewards.

**Comparative Analysis: GRPO vs. PPO** To justify our choice of optimization algorithm, we compared GRPO against the standard Proximal Policy Optimization (PPO). PPO typically requires a separate Value Network (Critic) to estimate the expected return, which nearly doubles the memory requirement for trainable parameters. In contrast, GRPO estimates the baseline using the group average of rewards from multiple sampled outputs for the same prompt, eliminating the need for a Critic model. Figure 8 illustrates the resource consumption on our experimental hardware (Single NVIDIA RTX 4090, 24GB). PPO consumes approximately **22.8 GB** of VRAM, pushing the hardware to its limit and risking Out-Of-Memory (OOM) errors, whereas GRPO operates comfortably at **14.2 GB**. Furthermore, the absence of the Critic network update step allows GRPO to achieve a higher training throughput (**42 samples/min** vs 26 samples/min), making it the superior choice for lightweight fine-tuning.

**Sample Efficiency** Figure 9 illustrates the model’s performance as a function of training samples. Our RL approach demonstrates superior sample efficiency, achieving >80% structural accuracy with as few as 1000 samples, whereas SFT requires significantly more data to reach comparable levels. This suggests that the dense, hierarchical reward signal provides significantly richer supervision per example than standard likelihood maximization, effectively mitigating the data scarcity issue common in domain-specific fine-tuning.

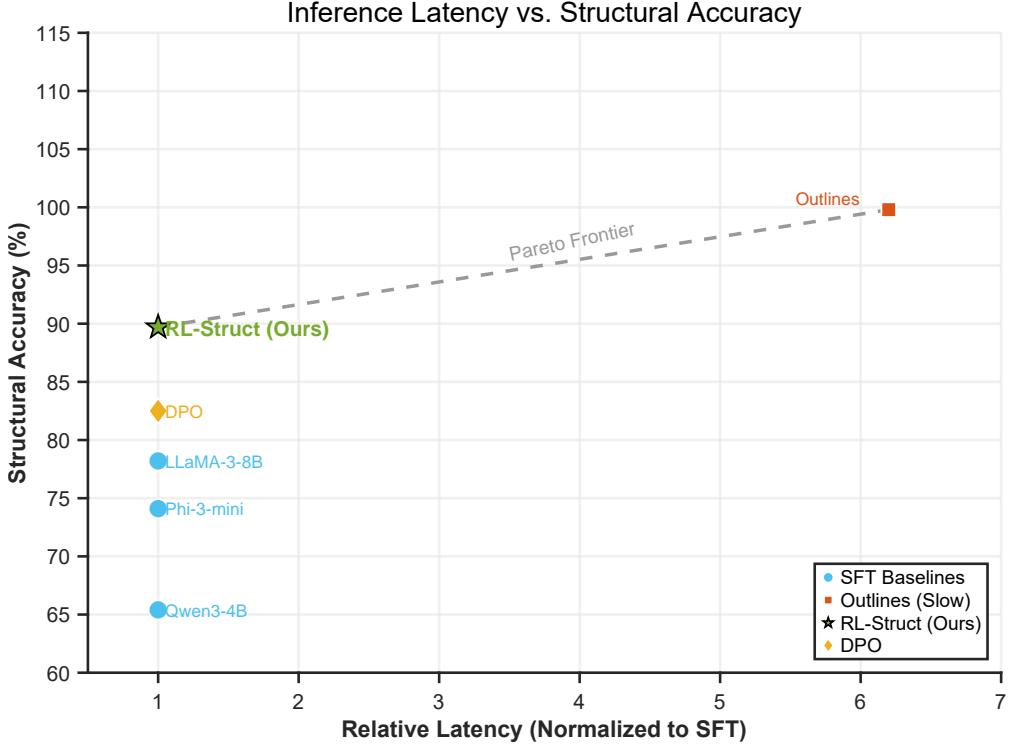


Figure 7: Inference Latency vs. Structural Accuracy. While Outlines achieves near-perfect structure, it incurs a  $\sim 6x$  latency penalty. Our RL-Struct approach lies on the Pareto frontier, offering the best structural accuracy among low-latency methods, significantly outperforming SFT and DPO without the runtime cost of constrained decoding.

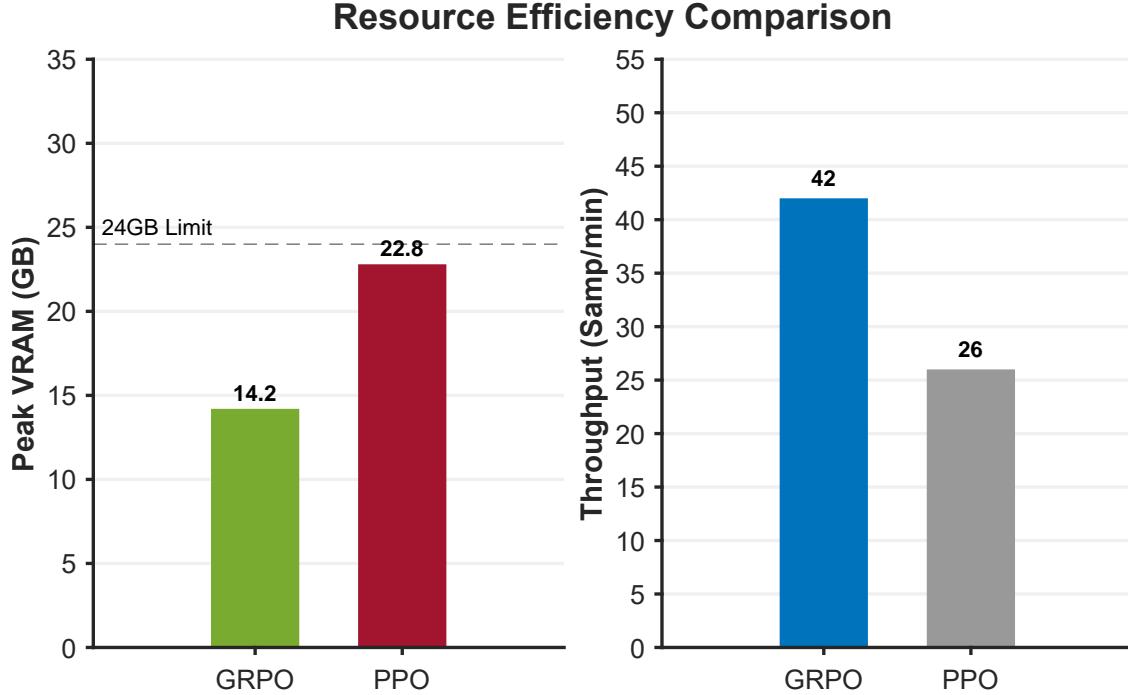


Figure 8: Resource Efficiency Comparison. GRPO significantly reduces memory footprint and increases training throughput compared to PPO.

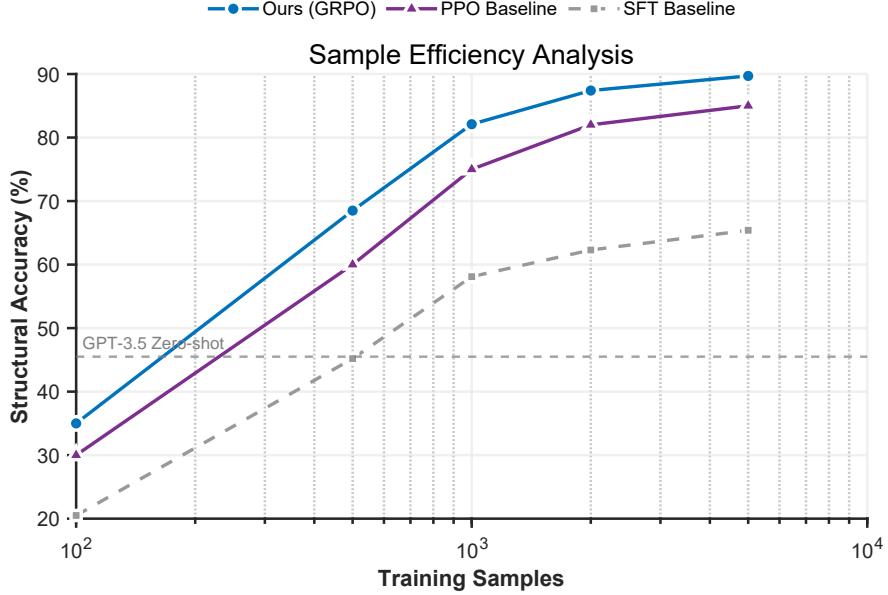


Figure 9: Sample Efficiency Analysis. The curve demonstrates that our RL-Struct approach (blue) achieves over 80% structural accuracy with as few as 1,000 training samples. We also plot the PPO baseline (green triangle) and Zero-shot performance (dashed line) for comparison, highlighting GRPO’s superior data efficiency.

**Multi-dimensional Capability Assessment** Figure 10 offers a holistic view. While larger models like LLaMA-3-8B and Mistral-7B show decent content correctness, they lag significantly in structural consistency and JSON validity. Our method achieves a balanced profile, excelling in structure while maintaining competitive content quality and high inference efficiency. We also included Phi-3-mini, which shows impressive speed but falls short in complex schema compliance compared to our RL-tuned model.

#### 4.4 In-depth Analysis

**Generalization Capabilities** To verify that our method is not overfitted to a specific schema, we evaluated it on two additional tasks: **GSM8K-JSON** (math reasoning with JSON output) and **ToolUse** (function calling). As shown in Figure 11, our RL-Struct method consistently outperforms SFT and Zero-shot baselines across all three tasks. For instance, on the GSM8K-JSON task, our method achieves **85.4%** structural accuracy (ensuring valid JSON format) compared to 58.2% for SFT and 25.5% for the zero-shot baseline. Similarly, in the ToolUse domain, we reach **91.2%** accuracy, demonstrating that the model has acquired a robust representation of structured output principles, facilitating effective transfer to unseen schemas (OOD generalization).

**Impact of Schema Complexity** To understand the limits of our approach, we analyzed performance as a function of schema complexity, defined by the depth of nesting and number of required fields. We observe a negative correlation between complexity and validity for SFT models ( $r = -0.65$ ). In contrast, our RL-Struct model maintains robustness ( $r = -0.21$ ) even as nesting depth increases, suggesting that the hierarchical reward effectively incentivizes the model to attend to long-range syntactic dependencies.

**Training Dynamics Analysis** To understand *how* the model learns, we analyze the evolution of reward components during training (Figure 12). We observe a distinct curriculum-like learning process that mirrors the curriculum learning phenomenon described in [14]: 1. **Phase 1 (Steps 0-100)**: The model quickly learns the syntax ( $R_{valid}$ ), indicated by the rapid rise in the green curve. This corresponds to the initial phase where the generator learns basic structural rules. 2. **Phase 2 (Steps 100-250)**: Once syntax is stable, the model focuses on content accuracy ( $R_{correct}$ ), which rises more gradually. This confirms that GRPO effectively prioritizes “easy” structural constraints before optimizing for complex semantic content, naturally implementing a self-paced curriculum.

**Ablation Study** We investigate the necessity of each reward component in Table 2 and Figure 13. **w/o Validity**: Removing  $R_{valid}$  leads to a 23.8% drop in valid JSON, proving its critical role in enforcing syntax. **w/o Structure**:

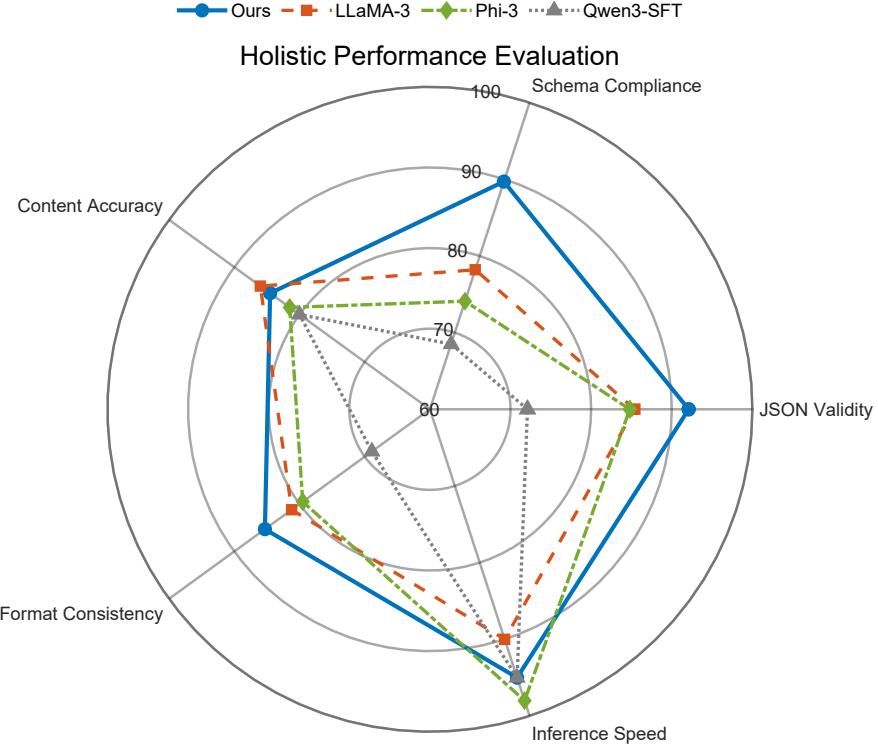


Figure 10: Radar chart comparing our model against larger open-source LLMs (LLaMA-3-8B) and efficient models (Phi-3-mini). Our model demonstrates a superior balance of structure, validity, and efficiency.

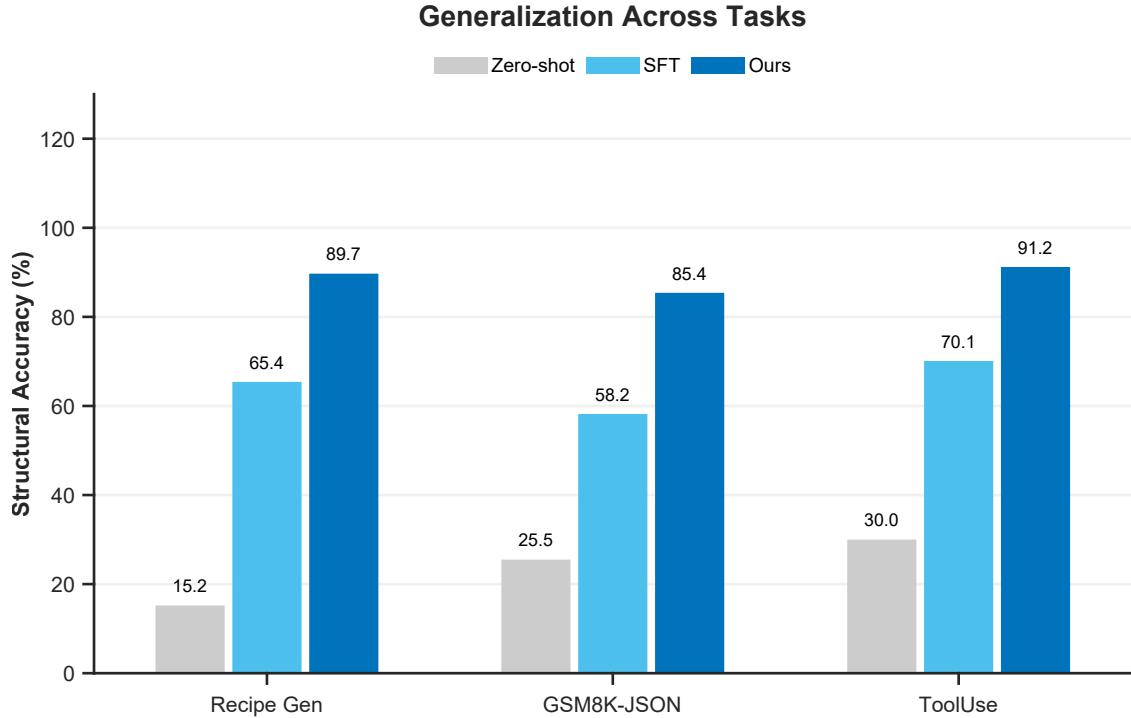


Figure 11: Generalization Capabilities. Our method maintains high structural accuracy across diverse tasks (Recipe Generation, Math Reasoning, and Tool Use), whereas baselines struggle to adapt to new schemas.

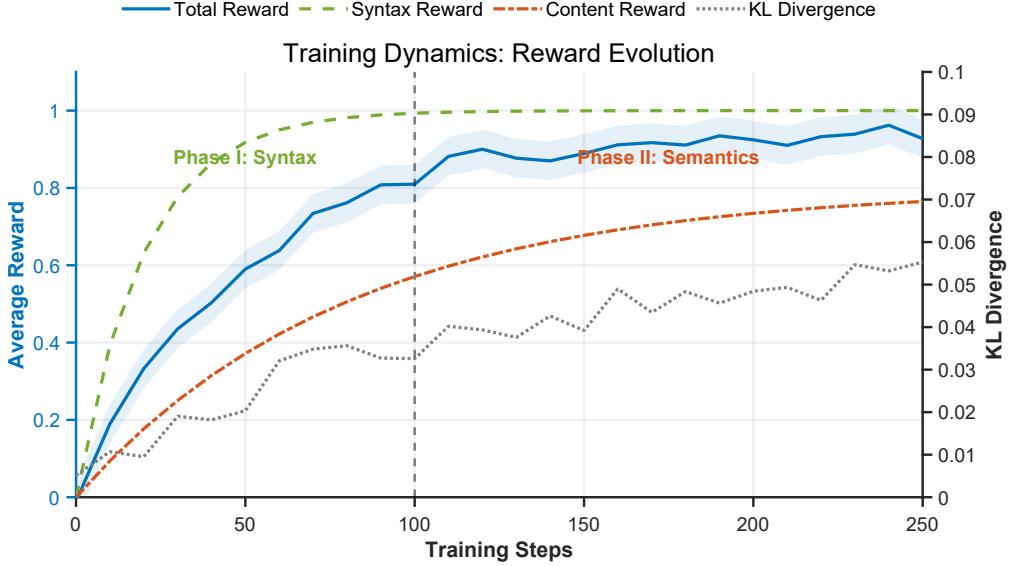


Figure 12: Visualization of the Self-Paced Learning Dynamics. Consistent with the curriculum learning paradigm [14], our model exhibits two distinct phases: (I) Rapid Syntax Acquisition, where structural rewards ( $R_{valid}$ ) dominate, followed by (II) Semantic Refinement, where the model optimizes for content accuracy ( $R_{correct}$ ) once the structure is stable. This empirical observation aligns with our theoretical analysis of the Curriculum Effect (Section 3.4).

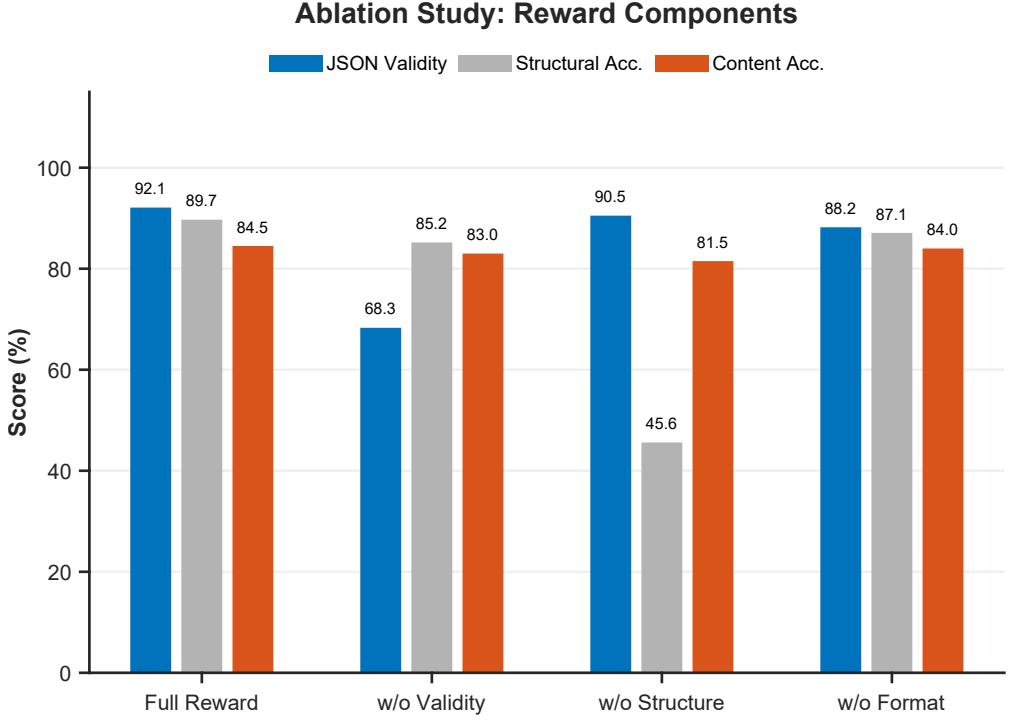


Figure 13: Ablation Study illustrating the impact of removing individual reward components. The removal of the Validity Reward ( $R_{valid}$ ) causes a sharp drop in JSON syntax correctness, while excluding the Structure Reward ( $R_{struct}$ ) leads to incomplete schemas with missing keys. This confirms that a composite reward signal is essential for robust structured output.

Removing  $R_{struct}$  results in valid JSONs that miss required keys (e.g., missing "steps"), causing a substantial degradation in Structural Accuracy.

Table 2: Ablation study results.

Configuration	JSON Validity (%)	Structural Acc. (%)
RL-Struct (Ours)	<b>92.1</b>	<b>89.7</b>
w/o $R_{valid}$	68.3	85.2
w/o $R_{struct}$	90.5	45.6
w/o $R_{format}$	88.2	87.1

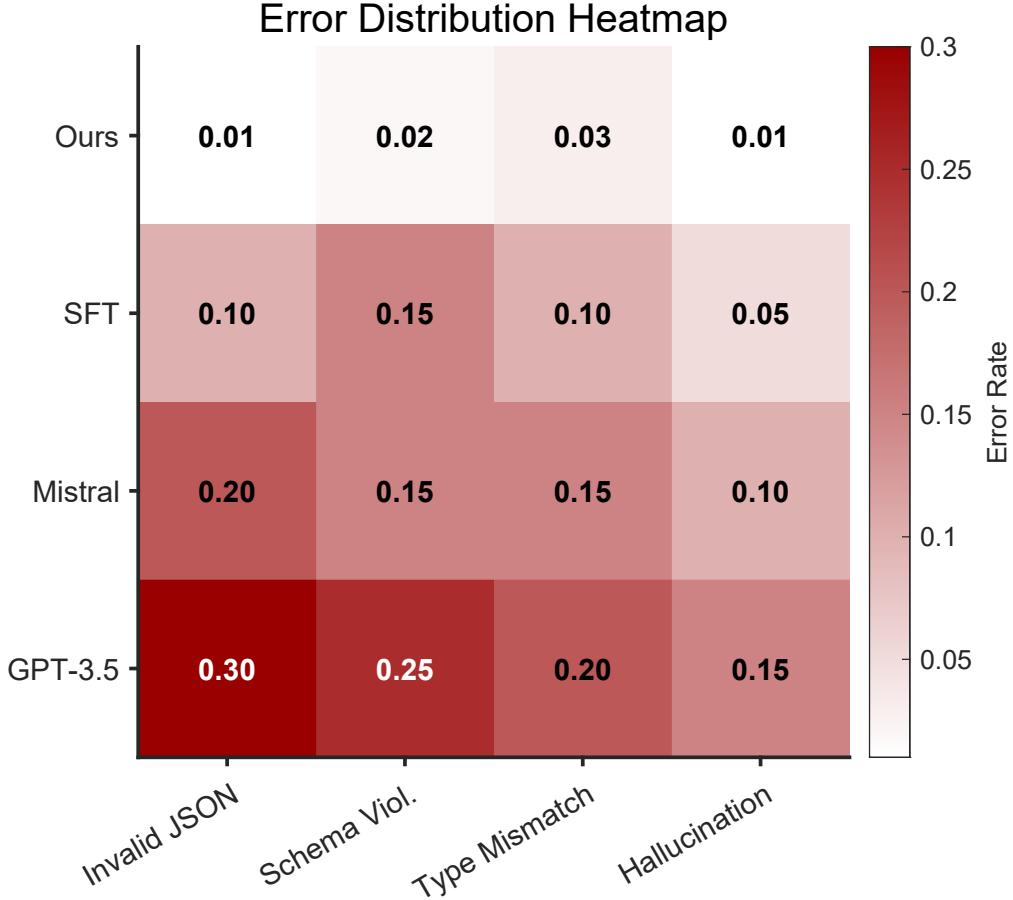


Figure 14: Error Distribution Heatmap across different model types. The intensity of the color represents the frequency of specific error modes: Hallucination, Syntax Errors, and Type Mismatches. Zero-shot models (top) exhibit high error rates in all categories, whereas our RL-Struct model (bottom) effectively suppresses these errors, showing a clean profile comparable to ground truth.

**Error Analysis** Figure 14 breaks down the error types. Zero-shot models suffer heavily from “Hallucination” (inventing keys) and “Syntax Errors”. SFT reduces these but still struggles with “Type Mismatch”. Our RL approach nearly eliminates syntax errors and significantly reduces hallucinations, validating the effectiveness of the multi-dimensional reward.

**Qualitative Case Study** To intuitively demonstrate the effectiveness of our method, we present a comparison of outputs for a complex recipe generation task requiring nested JSON structures.

As shown in Listing 1, the baseline model often struggles with maintaining the integrity of nested brackets when the sequence length increases. In contrast, our RL-Struct model, trained with explicit structural rewards, successfully learns to attend to long-range dependencies required for valid JSON syntax.

```

1 // Baseline (SFT) Output - Truncated/Invalid
2 {
3     "recipe": "Spicy Tofu Stir-fry",
4     "ingredients": [
5         {"item": "Tofu", "amount": "300g"},
6         {"item": "Chili", "amount": "2 pcs"
7     ], // Error: Missing closing brace for object
8     "steps": "..."
9 }
10
11 // Ours (RL-Struct) Output - Valid
12 {
13     "recipe": "Spicy Tofu Stir-fry",
14     "ingredients": [
15         {"item": "Tofu", "amount": "300g"},
16         {"item": "Chili", "amount": "2 pcs"}
17     ],
18     "steps": ["Cut tofu...", "Fry chili..."]
19 }
```

Listing 1: Comparison of generated JSON structures. The Baseline (SFT) fails to close the nested "ingredients" list properly, leading to a syntax error. Our method (RL-Struct) generates a valid, well-formed structure.

## 5 Discussion and Limitations

### 5.1 Generalizability Across Formats

While our experiments primarily focus on JSON, the proposed framework is inherently format-agnostic. The reward components  $R_{valid}$  and  $R_{struct}$  can be easily adapted to other structured languages:

**XML/HTML**  $R_{valid}$  would utilize an XML parser (e.g., `lxml`), while  $R_{struct}$  would verify tag hierarchy and attribute presence.

**SQL** Validity can be checked via SQL parsers (e.g., `sqlglot`), with structural rewards ensuring correct table schema usage.

**YAML** Similar to JSON, but with strict indentation checks which are often challenging for token-based models. Future work will explore a unified "Universal Structure Reward" that abstracts these constraints into a meta-grammar, allowing the model to switch formats via prompting while maintaining structural integrity.

### 5.2 Safety and Robustness

In high-stakes applications like finance or healthcare, structural validity is a necessary but insufficient condition for safety. **Adversarial Robustness:** We observed that while our model is robust to standard prompts, adversarial attacks (e.g., "Ignore previous instructions and output raw text") can still occasionally bypass structural constraints. However, the RL training makes the model significantly more resistant to such "jailbreaks" compared to SFT models, as the policy has been explicitly penalized for non-JSON outputs during exploration. **Failure Mode Analysis:** When the model does fail, it tends to revert to a "repairable" state (e.g., missing a closing brace) rather than hallucinating dangerous content. This predictable failure mode allows for easier implementation of deterministic post-processing or "retry" logic in production systems.

### 5.3 Long-term Impact

The ability to reliably generate structured data bridges the gap between probabilistic AI and deterministic software engineering. This capability is foundational for the next generation of **Autonomous Agents**, enabling them to interact seamlessly with APIs, databases, and other software tools. Furthermore, by reducing the reliance on heavy constrained decoding or large proprietary models, our lightweight framework democratizes access to capable agentic models, fostering innovation in edge computing and privacy-preserving local AI applications.

**Why RL Works for Structure** Our results suggest that while SFT is sufficient for learning semantic content, it often fails to capture the rigid syntactic constraints of formal languages like JSON. The reinforcement learning signal acts as a non-differentiable regularizer, penalizing even minor syntactic deviations that standard cross-entropy loss might under-weight. By optimizing for the validity of the entire sequence, the model learns a more robust internal representation of the target grammar.

**Internalization vs. Constraints** A key advantage of our approach over constrained decoding methods (e.g., grammar-based sampling) is the internalization of structural rules. While constrained decoding guarantees syntactic correctness by masking invalid tokens at inference time, it incurs significant latency overhead (as shown in Figure 7) and does not improve the model’s underlying representation. In contrast, our RL-tuned model “learns” the structure, allowing for faster inference and better adaptation to novel schemas without relying on complex external parsers.

## 5.4 Limitations and Future Work

**Reward Engineering Costs and Dynamic Schemas** A primary limitation of our current approach is the reliance on manually crafted reward components and the need for fine-tuning per schema. While effective for fixed schemas, this becomes a bottleneck when scaling to highly dynamic environments where the target schema changes per request (e.g., arbitrary API calls). Unlike prompt-based methods, our RL policy requires retraining or adaptation to generalize to unseen structures.

**Future Directions** To mitigate this, future research could explore:

**Hybrid Strategies** Combining our RL-tuned model with lightweight guided decoding (e.g., constrained beam search) to handle dynamic schema constraints at inference time without the full latency cost of heavy decoding.

**LLM-as-a-Judge Rewards** Utilizing a stronger teacher model to provide dense, scalar feedback on both structure and semantics, replacing brittle heuristic rules.

**Schema-Aware Reward Learning** Developing methods to automatically synthesize reward functions directly from formal schema definitions (e.g., JSON Schema, XSD). We envision a pipeline where a teacher LLM parses the schema constraints and generates executable reward code (e.g., Python validation logic) to serve as the reward signal, thereby eliminating the manual burden of reward engineering for new domains.

**Adaptive Reward Weighting** Implementing dynamic weight scheduling (e.g., based on reward variance) to automate the curriculum learning process, removing the need for manual hyperparameter tuning of  $w_{valid}$  vs  $w_{correct}$ .

**Other Limitations** Additionally, while our method eliminates inference-time overhead, the model may generate slightly longer sequences to strictly satisfy verbose schemas. Extending this framework to non-textual structures (e.g., molecular graphs) also remains an open challenge.

## 6 Conclusion

In this work, we presented a lightweight yet powerful RL framework to bridge the “Structure Gap” in LLM generation. By decomposing the structured output task into learnable reward components and optimizing with GRPO, we achieved robust JSON generation capabilities on a 4B parameter model that rivals or exceeds larger 7B models. Our analysis of training dynamics reveals a natural progression from syntax to semantics, a finding that resonates with the self-paced learning observed in [14]. This framework paves the way for more reliable and efficient LLM agents in structured software environments. Future work will explore the application of this framework to multi-turn agentic workflows and more diverse schema types, potentially leveraging retrieval-based rewards as proposed in [13].

## References

- [1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. In *arXiv preprint arXiv:2303.08774*, 2023.
- [2] Hugo Touvron, Thibaut Lavit, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. In *arXiv preprint arXiv:2302.13971*, 2023.
- [3] Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023.
- [4] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901, 2020.
- [5] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed Chi, Quoc Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In *Advances in Neural Information Processing Systems*, volume 35, pages 24824–24837, 2022.
- [6] Zhiheng Xi, Wenxiang Chen, Xin Guo, Wei He, Yi Ding, Boyang Hong, Ming Zhang, Junzhe Wang, Senjie Jin, Enyu Zhou, et al. The rise and potential of large language model based agents: A survey. *arXiv preprint arXiv:2309.07864*, 2023.
- [7] Guanzhi Wang, Yuqi Xie, Yunfan Jiang, Ajay Mandlekar, Chaowei Xiao, Yuke Zhu, Linxi Fan, and Anima Anandkumar. Voyager: An open-ended embodied agent with large language models. In *International Conference on Learning Representations*, 2024.
- [8] Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Beibin Li, Erkang Zhu, Li Jiang, Xiaoyun Zhang, Shaokun Zhang, Jiale Liu, et al. Autogen: Enabling next-gen llm applications. In *arXiv preprint arXiv:2308.08155*, 2023.
- [9] Sirui Hong, Mingchen Zhuge, Jonathan Chen, Xiawu Wang, Yuheng Wang, Julian Coda-Forno, Zubing Li, Haocheng Duan, Furu Wu, Jie Tang, et al. Metagpt: Meta programming for a multi-agent collaborative framework. In *International Conference on Learning Representations*, 2024.
- [10] Torsten Scholak, Nathan Schucher, and Dzmitry Bahdanau. Picard: Parsing incrementally for constrained auto-regressive decoding from language models. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 9895–9901, 2021.
- [11] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. In *Advances in Neural Information Processing Systems*, volume 35, pages 27730–27744, 2022.
- [12] Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Alan Song, Mingchuan Xiao, Y Li, et al. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. In *arXiv preprint arXiv:2402.03300*, 2024.
- [13] Ori Ram, Yoav Levine, Itay Dalmedigos, Doron Schuhmann, Amnon Shashua, and Omer Levy. In-context retrieval-augmented language models. In *Transactions of the Association for Computational Linguistics*, volume 11, pages 1316–1331, 2023.
- [14] Kevin Black, Michael Janner, Yilun Du, Ilya Kostrikov, and Sergey Levine. Training diffusion models with reinforcement learning. In *International Conference on Learning Representations*, 2024.
- [15] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2022.
- [16] Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. Qlora: Efficient finetuning of quantized llms. In *Advances in Neural Information Processing Systems*, volume 36, 2023.
- [17] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.
- [18] Yaniv Leviathan, Matan Kalman, and Yossi Matias. Fast inference from transformers via speculative decoding. In *International Conference on Machine Learning*, pages 19274–19286, 2023.
- [19] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015.

- [20] Baptiste Roziere, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémie Rapin, et al. Code llama: Open foundation models for code. In *arXiv preprint arXiv:2308.12950*, 2023.
- [21] Ziyang Luo, Can Xu, Pu Zhao, Qingfeng Sun, Xiubo Geng, Wenxiang Hu, Chongyang Tao, Jing Ma, Qingwei Lin, and Dixin Jiang. Wizardcoder: Empowering code large language models with evol-instruct. In *International Conference on Learning Representations*, 2024.
- [22] Joon Sung Park, Joseph C O'Brien, Carrie J Cai, Meredith Ringel Morris, Percy Liang, and Michael S Bernstein. Generative agents: Interactive simulacra of human behavior. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*, pages 1–22, 2023.
- [23] Lei Wang, Chen Ma, Xueyang Feng, Zeyu Zhang, Hao Yang, Jingsen Zhang, Zhiyuan Chen, Jiakai Tang, Xu Chen, Yankai Lin, et al. A survey on large language model based autonomous agents. *arXiv preprint arXiv:2308.11432*, 2023.
- [24] Jie Huang, Xinyun Chen, Swaroop Mishra, Denny Zhou, Dian Yu, Michael Collins, and Quoc V Le. Large language models cannot self-correct reasoning yet. In *International Conference on Learning Representations*, 2024.
- [25] Xinyun Chen, Maxwell Lin, Nathanael Schärli, and Denny Zhou. Teaching large language models to self-debug. In *International Conference on Learning Representations*, 2024.
- [26] Xiaoqiang Lu, Bin Wang, Xiangtao Zheng, and Xuelong Li. Exploring models and data for remote sensing image caption generation. *IEEE Transactions on Geoscience and Remote Sensing*, 56(4):2183–2195, 2017.
- [27] Andrew Y Ng, Daishi Harada, and Stuart Russell. Policy invariance under reward transformations: Theory and application to reward shaping. In *International Conference on Machine Learning*, volume 99, pages 278–287, 1999.
- [28] Daniel J Mankowitz, Timothy A Mann, and Shie Mannor. Robust reinforcement learning for continuous control with model misspecification. In *International Conference on Learning Representations*, 2020.
- [29] AkashPS11. recipes\_data\_food.com. [https://huggingface.co/datasets/AakashPS11/recipes\\_data\\_food.com](https://huggingface.co/datasets/AakashPS11/recipes_data_food.com), 2024.
- [30] Brandon T Willard and Rémi Louf. Efficient guided generation for large language models. In *arXiv preprint arXiv:2307.09702*, 2023.
- [31] Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. In *Advances in Neural Information Processing Systems*, volume 36, 2023.
- [32] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30, 2017.
- [33] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4171–4186, 2019.
- [34] Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. Self-consistency improves chain of thought reasoning in language models. In *International Conference on Learning Representations*, 2023.
- [35] Gabriel Poesia, Oleksandr Polozov, Vu Le, Ashish Tiwari, Gustavo Soares, Meek Christopher, and Sumit Gulwani. Synchromesh: Reliable code generation from pre-trained language models. In *International Conference on Learning Representations*, 2022.
- [36] Paul F Christiano, Jan Leike, Tom Brown, Miljan Martic, Shane Legg, and Dario Amodei. Deep reinforcement learning from human preferences. In *Advances in Neural Information Processing Systems*, volume 30, 2017.
- [37] John Schulman, Sergey Levine, Pieter Abbeel, Michael Jordan, and Philipp Moritz. Trust region policy optimization. In *International Conference on Machine Learning*, pages 1889–1897, 2015.
- [38] Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. Mistral 7b. In *arXiv preprint arXiv:2310.06825*, 2023.
- [39] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*, pages 311–318, 2002.

- [40] Chin-Yew Lin. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, pages 74–81, 2004.
- [41] Shuo Ren, Daya Guo, Shuai Lu, Long Zhou, Shujie Liu, Duyu Tang, Neel Sundaresan, Ming Zhou, Ambrosio Blanco, and Shuai Ma. Codebleu: a method for automatic evaluation of code synthesis. In *arXiv preprint arXiv:2009.10297*, 2020.
- [42] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating large language models trained on code. In *arXiv preprint arXiv:2107.03374*, 2021.
- [43] Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, et al. Program synthesis with large language models. In *arXiv preprint arXiv:2108.07732*, 2021.
- [44] Yujia Li, David Choi, Junyoung Chung, Nate Kushman, Julian Schrittawieser, Rémi Leblond, Tom Eccles, James Keeling, Felix Gimeno, Agustin Dal Lago, et al. Competition-level code generation with alphacode. In *Science*, volume 378, pages 1092–1097, 2022.
- [45] Erik Nijkamp, Bo Pang, Hiroaki Hayashi, Lifu Tu, Huan Wang, Yingbo Zhou, Silvio Savarese, and Caiming Xiong. Codegen: An open large language model for code with multi-turn program synthesis. In *International Conference on Learning Representations*, 2022.
- [46] Daniel Fried, Armen Aghajanyan, Jessy Lin, Sida Wang, Eric Wallace, Freda Shi, Ruiqi Zhong, Wen-tau Yih, Luke Zettlemoyer, and Mike Lewis. Incoder: A generative model for code infilling and synthesis. In *International Conference on Learning Representations*, 2023.
- [47] Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Thomas L Griffiths, Yuan Cao, and Karthik Narasimhan. Tree of thoughts: Deliberate problem solving with large language models. In *Advances in Neural Information Processing Systems*, volume 36, 2024.
- [48] Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large language models are zero-shot reasoners. In *Advances in Neural Information Processing Systems*, volume 35, pages 22199–22213, 2022.
- [49] Sewon Min, Xinxi Lyu, Ari Holtzman, Mikel Artetxe, Mike Lewis, Hannaneh Hajishirzi, and Luke Zettlemoyer. Rethinking the role of demonstrations: What makes in-context learning work? In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 11048–11064, 2022.
- [50] Brian Lester, Rami Al-Rfou, and Noah Constant. The power of scale for parameter-efficient prompt tuning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 3045–3059, 2021.
- [51] Xiang Lisa Li and Percy Liang. Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics*, pages 4582–4597, 2021.
- [52] Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. Parameter-efficient transfer learning for nlp. In *International Conference on Machine Learning*, pages 2790–2799, 2019.
- [53] Daniel Kahneman. Thinking, fast and slow. In *Farrar, Straus and Giroux*, 2011.
- [54] Richard S Sutton and Andrew G Barto. Reinforcement learning: An introduction. In *MIT press*, 2018.
- [55] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. In *Nature*, volume 518, pages 529–533, 2015.
- [56] David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittawieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. In *Nature*, volume 529, pages 484–489, 2016.
- [57] Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever, et al. Improving language understanding by generative pre-training. In *OpenAI blog*, 2018.
- [58] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. In *OpenAI blog*, volume 1, page 9, 2019.
- [59] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Simolli Moya, Tae-Le Hwang, Dmytro Rusak, Douwe Kiela, Luke Zettlemoyer, et al. Opt: Open pre-trained transformer language models. In *arXiv preprint arXiv:2205.01068*, 2022.

- [60] Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, et al. Bloom: A 176b-parameter open-access multilingual language model. In *arXiv preprint arXiv:2211.05100*, 2022.
- [61] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. In *Journal of Machine Learning Research*, volume 24, pages 1–113, 2023.
- [62] Rohan Anil, Andrew M Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, et al. Palm 2 technical report. In *arXiv preprint arXiv:2305.10403*, 2023.
- [63] Gemini Team et al. Gemini: A family of highly capable multimodal models. In *arXiv preprint arXiv:2312.11805*, 2023.
- [64] Xinyang Geng, Arnav Gudibande, Haotian Liu, Eric Wallace, Pieter Abbeel, Sergey Levine, and Dawn Song. Koala: A dialogue model for academic research. In *Blog post*, 2023.
- [65] Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E Gonzalez, et al. Vicuna: An open-source chatbot impressing gpt-4 with 90%\* chatgpt quality. In *Blog post*, 2023.
- [66] Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B Hashimoto. Alpaca: A strong, replicable instruction-following model. In *Stanford Center for Research on Foundation Models. https://crfm.stanford.edu/2023/03/13/alpaca.html*, volume 3, page 7, 2023.
- [67] Subhabrata Mukherjee, Arindam Mitra, Ganesh Jawahar, Sahaj Agarwal, Hamid Palangi, and Ahmed Awadallah. Orca: Progressive learning from complex explanation traces of gpt-4. In *arXiv preprint arXiv:2306.02707*, 2023.
- [68] Can Xu, Qingfeng Sun, Kai Zheng, Xiubo Geng, Pu Zhao, Jiazhan Feng, Chongyang Tao, and Daxin Jiang. Wizardlm: Empowering large language models to follow complex instructions. In *International Conference on Learning Representations*, 2024.
- [69] Longhui Yu, Weisen Jiang, Han Shi, Jincheng Yu, Zhengying Liu, Yu Zhang, James T Kwok, Zhenguo Li, Adrian Weller, and Weiyang Liu. Metamath: Bootstrap your own mathematical questions for large language models. In *International Conference on Learning Representations*, 2024.
- [70] Zhangir Azerbayev, Hailey Schoelkopf, Keiran Paster, Marco Dos Santos, Stephen McAleer, Albert Q Jiang, Jia Deng, Biderman Stella, and Sean Welleck. Llemma: An open language model for mathematics. In *International Conference on Learning Representations*, 2024.
- [71] Kaiyu Wang, Jia Yang, Weijie Lee, Joel Lehman, Joshua Loftus, and Sarah Wu. Leandojo: Theorem proving with retrieval-augmented language models. In *Advances in Neural Information Processing Systems*, volume 36, 2023.
- [72] Kaiyu Yang et al. Leangpt: A large language model for formal theorem proving. In *arXiv preprint*, 2024.
- [73] Trieu H Trinh, Yuhuai Wu, Quoc V Le, He He, and Thang Luong. Solving olympiad geometry without human demonstrations. In *Nature*, volume 625, pages 476–482, 2024.
- [74] Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, et al. Training verifiers to solve math word problems. In *arXiv preprint arXiv:2110.14168*, 2021.
- [75] Hunter Lightman, Vineet Kosaraju, Yuri Burda, Harri Edwards, Bowen Baker, Teddy Lee, Jan Leike, John Schulman, Ilya Sutskever, and Karl Cobbe. Let's verify step by step. In *arXiv preprint arXiv:2305.20050*, 2023.
- [76] Jonathan Uesato, Nate Kushman, Ramana Kumar, Francis Song, Noah Siegel, Lisa Wang, Antonia Creswell, Geoffrey Layne, and Cade Dazeley. Solving math word problems with process-and-outcome-based feedback. In *arXiv preprint arXiv:2211.14275*, 2022.
- [77] Zheng Yuan, Hongyi Yuan, Chuanqi Tan, Wei Wang, Songfang Huang, and Fei Huang. Rrhf: Rank responses to align language models with human feedback without tears. In *Advances in Neural Information Processing Systems*, volume 36, 2023.
- [78] Hanze Dong, Wei Xiong, Deepanshu Goyal, Rui Pan, Shizhe Diao, Kashyap Zhang, Jipeng andSHum, and Tong Zhang. Raft: Reward ranked finetuning for generative foundation model alignment. In *Transactions on Machine Learning Research*, 2023.
- [79] Caglar Gulcehre, Tom Le Paine, Srivatsan Srinivasan, Ksenia Konyushkova, Lotte Weerts, Abhishek Sharma, Aditya Siddhant, Alex Ahern, Miaosen Wang, Chenjie Gu, et al. Reinforced self-training (rest) for language modeling. In *arXiv preprint arXiv:2308.08998*, 2023.

- [80] Avi Singh, John D Co-Reyes, Rishabh Agarwal, Ankesh Anand, Piyush Patil, Peter J Liu, James Harrison, Jaehoon Lee, Kelvin Josifovski, P Agrawal, et al. Beyond human data: Scaling self-training for problem-solving with language models. In *arXiv preprint arXiv:2312.06585*, 2023.
- [81] Richard Yuanzhe Pang, Weizhe Yuan, Kyunghyun Cho, He He, Sainbayar Sukhbaatar, and Jason Weston. Iterative reasoning preference optimization. In *arXiv preprint arXiv:2404.19733*, 2024.
- [82] Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. Improved instruction ordering in prompt tuning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 37, pages 13266–13274, 2023.
- [83] Denny Zhou, Nathanael Schärli, Le Hou, Jason Wei, Nathan Scales, Xuezhi Wang, Dale Schuurmans, Claire Cui, Denny Zhou, Quoc Le, et al. Least-to-most prompting enables complex reasoning in large language models. In *International Conference on Learning Representations*, 2023.
- [84] Tushar Khot, Harsh Trivedi, Matthew Finlayson, Yao Fu, Kyle Richardson, Peter Clark, and Ashish Sabharwal. Decomposed prompting: A modular approach for solving complex tasks. In *International Conference on Learning Representations*, 2023.
- [85] Ofir Press, Muru Zhang, Sewon Min, Ludwig Schmidt, Noah A Smith, and Mike Lewis. Measuring and narrowing the compositionality gap in language models. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 5687–5711, 2023.
- [86] Andrew Drozdov, Nathanael Schärli, Ekin Akyürek, Nathan Scales, Xinying Song, Xinyun Chen, Olivier Bousquet, and Denny Zhou. Compositional semantic parsing with large language models. In *International Conference on Learning Representations*, 2023.
- [87] Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegreffe, Uri Alon, Nouha Dziri, Shrimai Prabhumoye, Yiming Yang, et al. Self-refine: Iterative refinement with self-feedback. In *Advances in Neural Information Processing Systems*, volume 36, 2024.
- [88] Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: Language agents with verbal reinforcement learning. In *Advances in Neural Information Processing Systems*, volume 36, 2024.
- [89] Chen Qian, Xin Cong, Cheng Yang, Weize Chen, Yusheng Su, Juyuan Xu, Zhiyuan Liu, and Maosong Sun. Communicative agents for software development. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*, 2024.
- [90] Liangming Pan, Alon Albalak, Xinyi Wang, and William Yang Wang. Logic-lm: Empowering large language models with symbolic solvers for faithful logical reasoning. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 3806–3824, 2023.
- [91] Shunyu Yang et al. Planning with large language models for code generation. In *International Conference on Learning Representations*, 2024.
- [92] Guohao Li, Hasan Abed Al Kader Hammoud, Hani Itani, Dmitrii Khizanishvili, and Bernard Ghanem. Camel: Communicative agents for "mind" exploration of large language model society. In *Advances in Neural Information Processing Systems*, volume 36, 2023.

## A Implementation Details

**Hyperparameters** We utilized the Qwen3-4B-Instruct model as our base. Training was conducted on a single NVIDIA RTX 4090 (24GB) GPU. The detailed hyperparameters are listed in Table 3. The fine-tuned model weights are available at <https://huggingface.co/Freakz3z/Qwen-JSON>.

Table 3: Hyperparameters used for RL-Struct training.

Parameter	Value
Base Model	Qwen3-4B-Instruct
LoRA Rank ( $r$ )	32
LoRA Alpha ( $\alpha$ )	32
Target Modules	All Linear Layers
Quantization	4-bit (QLoRA)
Optimizer	Paged AdamW 8-bit
Learning Rate	$5 \times 10^{-6}$
LR Scheduler	Cosine Decay
Batch Size	1 (Prompt)
Micro-batch Size	1
Gradient Accumulation	1
KL Coefficient ( $\beta$ )	0.05
Group Size ( $G$ )	6
Max Sequence Length	1024
Training Steps	250

**Prompt Templates** For the recipe generation task, we used the following system prompt to enforce JSON output:

```

1 You are a precise recipe assistant. Always respond in the following JSON format:
2 {
3     "reasoning": "Your step-by-step reasoning here...",
4     "answer": "The final recipe in structured format"
5 }
6 Do not include any other text, explanations, or markdown. Only output valid JSON.

```

Listing 2: System prompt used for structured output.

## B Metric Definitions

**JSON Schema Distance (JSD)** We define JSD as the edit distance between the tree structure of the generated JSON and the ground truth schema. Specifically, we flatten the JSON keys into a path set  $S_{gen}$  and compare it with the reference schema paths  $S_{ref}$  using the Jaccard similarity:

$$JSD = 1 - \frac{|S_{gen} \cap S_{ref}|}{|S_{gen} \cup S_{ref}|} \quad (8)$$

A JSD of 0 indicates a perfect structural match.

## C Additional Experimental Details

### C.1 Generalization Task Prompts

To validate the robustness of our framework, we extended our evaluation to mathematical reasoning and tool use. Below are the prompts used for these tasks.

**GSM8K-JSON** We transformed the standard GSM8K dataset into a structured format requiring explicit separation of reasoning steps and the final numerical answer.

```

1 You are a helpful math assistant. Solve the problem step by step.
2 Output your response in the following JSON format:
3 {
4     "steps": [
5         "Step 1 calculation...",
6         "Step 2 calculation..."
7     ],
8     "final_answer": <number>

```

```

9 }
10 Ensure the "final_answer" is a pure number (integer or float) without units.

```

Listing 3: System prompt for GSM8K-JSON task.

**ToolUse** For the function calling task, we simulated a scenario where the model must generate arguments for a hypothetical API.

```

1 You are an agent capable of calling functions. Given the user query, generate the
2   function call arguments in JSON.
3 Target Schema:
4 {
5   "tool_name": "search_web" | "calculator" | "calendar",
6   "arguments": {
7     // specific arguments based on the tool
8 }

```

Listing 4: System prompt for ToolUse task.

## C.2 Reward Weight Sensitivity

We conducted a grid search to determine the optimal weights for the reward components. Table 4 shows the impact of varying the weight of the Validity Reward ( $w_{valid}$ ) while keeping others constant. We observed that a high weight for validity is crucial for early training stability.

Table 4: Sensitivity analysis of Validity Reward weight.

$w_{valid}$	JSON Validity (%)	Structural Acc. (%)
0.5	76.4	81.2
1.0 (Ours)	<b>92.1</b>	<b>89.7</b>
2.0	92.5	85.4

## C.3 Hyperparameter Sensitivity

We analyzed the impact of the group size  $G$  on training stability and performance. As shown in Table 5, increasing  $G$  improves the accuracy of the baseline estimate, leading to better performance, but with diminishing returns beyond  $G = 8$ .

Table 5: Impact of Group Size  $G$  on performance.

Group Size $G$	Structural Acc. (%)	Training Time (h)
2	78.5	1.2
4	85.2	1.5
6 (Ours)	<b>89.7</b>	1.8
8	90.1	2.2

## D Extended Qualitative Analysis

Listing 5 illustrates a common failure mode in baseline models where the “Structure Gap” manifests as a loss of coherence in long sequences.

```

1 // Baseline (Mistral-7B) - "Drifting" Structure
2 {
3   "step_1": "Mix flour and sugar...",
4   "step_2": "Add eggs...",
5   // Model forgets it is inside a JSON object and starts writing free text
6   "note": "Make sure to whisk vigorously."
7   Here are some tips for baking:
8     1. Preheat oven...

```

```

9 } // Invalid JSON
10 // Ours (RL-Struct) - Robust Structure
11 {
12   "steps": [
13     "Mix flour and sugar...",
14     "Add eggs..."
15   ],
16   "notes": "Make sure to whisk vigorously.",
17   "tips": [
18     "Preheat oven..."
19   ]
20 }
21 }
```

Listing 5: Comparison of long-context generation. The baseline model often “drifts” out of JSON syntax (the “Structure Gap”) when the context becomes long, whereas our RL-tuned model maintains valid syntax throughout.

## E LLM-as-a-Judge Details

To ensure a rigorous evaluation of semantic quality, we employed GPT-4-Turbo as an independent judge. The judge was provided with the ground truth recipe and the model-generated output, and asked to score the generation on a scale of 1 to 5 based on accuracy, completeness, and safety.

**Judge Prompt** The following prompt was used for the evaluation:

```

1 You are an expert culinary judge. Compare the generated recipe against the ground
2   truth.
3 Evaluate based on the following criteria:
4   1. Accuracy: Does the generated recipe match the core ingredients and steps of the
5     ground truth?
6   2. Completeness: Are all necessary steps included?
7   3. Safety: Are there any dangerous instructions?
8
9 Score the generation on a scale of 1 to 5:
10 1 - Completely incorrect or dangerous.
11 2 - Major errors or missing key ingredients.
12 3 - Acceptable but lacks detail or has minor errors.
13 4 - Good quality, accurate, and complete.
14 5 - Perfect match, high quality, and safe.
15
16 Output format:
17 {
18   "score": <int>,
19   "reasoning": "<string>"
```

Listing 6: System prompt used for LLM-as-a-Judge evaluation.