

Online Rubrics Elicitation from Pairwise Comparisons

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Abstract

Rubrics provide a flexible way to train LLMs on open-ended long-form answers where verifiable rewards are not applicable and human preferences provide coarse signals. Prior work shows that reinforcement learning with rubric-based rewards leads to consistent gains in LLM post-training. Most existing approaches rely on rubrics that remain static over the course of training. Such static rubrics, however, are vulnerable to reward-hacking type behaviors and fail to capture emergent desiderata that arise during training. We introduce Online Rubrics Elicitation (OnlineRubrics), a method that dynamically curates evaluation criteria in an *online* manner through pairwise comparisons of responses from current and reference policies. This online process enables continuous identification and mitigation of errors as training proceeds. Empirically, this approach yields consistent improvements of up to 8% over training exclusively with static rubrics across AlpacaEval, GPQA, ArenaHard as well as the validation sets of expert questions and rubrics. We qualitatively analyze the elicited criteria and identify prominent themes such as transparency, practicality, organization, and reasoning.

1. Introduction

Recent advances in reinforcement learning are reshaping the traditional post-training recipe. Guo et al. [17] demonstrated that supervised fine-tuning on instructions can be skipped altogether, with policies (e.g. R1-Zero) trained directly via reinforcement learning, disrupting the way researchers think about post-training. Since then, much of the focus has shifted towards reinforcement learning. However, R1-Zero was trained only using verifiable rewards; the final response is easily gradable, think of a number or code snippet with unit tests, which is only applicable to limited domains.

To accommodate broader settings, rubric-based scoring for reinforcement learning emerges as an alternative way for reward modeling, particularly for long-form responses [2, 16, 19, 37]. Rubrics are comprised of a list of input-specific criteria that characterizes an ideal response; one example criterion in the finance domain is “*States shocking basis causes nonlinear effects in margin calls*”. Each criterion has an importance weight: satisfying positively weighted criteria yields reward, while satisfying negatively weighted criteria yields penalty. During training, an LLM-based grader evaluates a response against each criterion in the rubric, producing binary satisfaction scores; and the overall score is the weighted average of these grades. This framework extends reinforcement learning to both verifiable and non-verifiable aspects of responses, spanning generalist and expert domains alike.

Rubrics often emphasize the desired behaviors with less coverage of undesired properties. *Offline rubrics* created a priori, human-written or synthetic, cannot realistically cover every unexpected (and desired) pattern. Fixed checklists [38] to enforce generally helpful patterns e.g. truthfulness, instruction following or relevance, fall short in preventing nuanced errors. For example, Huang et al. [19] identifies “self-praising” as one emerging pattern during reinforcement learning from rubrics, think of including “*The following advice is the most relevant*” as part of the response; these praises often fool the LLM-based grader into believing that the given response is indeed relevant. Such patterns are especially difficult for generic “catch-all” rubrics to reveal when they are sample-specific. Moreover, correct traits in some generations can go unnoticed if not readily rewarded by the existing offline rubrics.

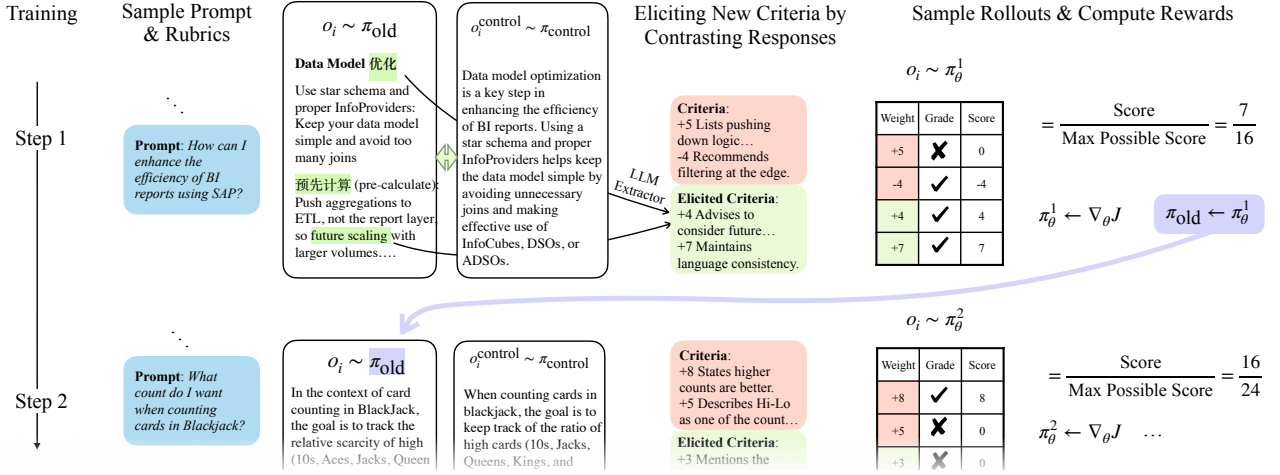


Figure 1: At any step during training, OnlineRubrics starts off by considering a pair of responses, one of which is from the current policy before updates and another from a *control* model e.g. reference model. We follow with LLM-based rubrics elicitation and deduplication steps to generate a set of *elicited criteria*. These criteria along with existing criteria (e.g. human-written or synthetic) are used to create the reward in the policy gradient algorithm.

We introduce OnlineRubrics, a framework for eliciting evaluation criteria dynamically via pairwise comparisons. OnlineRubrics leverages a pair of responses in creating additional criteria where the responses are sampled from the current policy and a control model. Our work, as depicted in Figure 1, is inspired by the large body of literature on preference learning [1, 13, 31] and pairwise reward modeling [7, 27, 36]. While LLMs are imperfect judges of quality [15], we found that pairwise comparisons are easier to make for the models when identifying new criteria than directly making a quality assessment or creating new criteria by considering a single response (point-wise elicitation). The additional criteria simply augments the existing rubric, enabling seamless integration of OnlineRubrics with any rubric-based scoring mechanism.

In training and evaluating our approach, we curate two datasets for expert (scientific use-cases) and generalist domains. We additionally conduct out-of-distribution evaluations using public benchmarks, comparing different approaches to reward estimation. OnlineRubrics results in absolute gains of up to 25% over the initial instruct model across various benchmarks including GPQA-Diamond [30], GSM8K Cobbe et al. [8], AlpacaEval Li et al. [22], and Arena-Hard [21].

2. Related Work

Reward Modeling The dominant paradigm in LLM alignment is to learn a reward function from feedback. Foundational work in Reinforcement Learning from Human Feedback (RLHF) established the use of pairwise preference comparisons—preferred over less robust pointwise scores—to train an explicit reward model [27, 36]. This process was later simplified by methods like Direct Preference Optimization (DPO; Rafailov et al. [29]), which bypasses the explicit reward model and optimizes policies directly on preference data. Methods for generating feedback have also advanced: Bai et al. [4], for example, pioneered the use of AI feedback (RLAIF) by leveraging a fixed set of principles for model self-feedback. More recently, research has focused on improving the reward model’s intrinsic capability. Liu et al. [24] established inference-time scaling laws for generalist reward models, boosting performance with added computation, while Whitehouse et al. [40] incentivizes faithful evaluation by training LLM judges to generate reasoning.

While preference-based rewards provide flexible but often fuzzy signals, verifiable rewards offer exact supervision whenever the outcome can be automatically checked. Reinforcement Learning with Verifiable Rewards (RLVR) improves reasoning by optimizing policies against automatically checkable outcomes, such as numeric answers or unit-tested code. Recent work has shown its effectiveness across various domains: DeepSeek-R1 [17] and General-Reasoner [26] achieved strong results on benchmarks such as GSM8K [8], MMLU [18], and GPQA [30]. In

medicine, Zhang et al. [41] enabled a 3B model to reach expert-level performance. Foundational studies confirm that RLVR incentivizes correct reasoning processes, not just correct answers Wen et al. [39]. Despite these strengths, RLVR does not extend to open-ended domains where correctness cannot be automatically verified.

Multi-Objective Alignment Beyond single-reward formulations, recent research has explored *multi-objective RLHF* approaches that optimize across several criteria simultaneously. Safe RLHF [10] decouples helpfulness and harmlessness rewards and balances them using constrained optimization. Gradient-Adaptive Policy Optimization (GAPO) [23] employs multiple-gradient descent to achieve Pareto-optimal trade-offs across competing objectives, while Lu et al. [25] proposes dynamically adjusting reward weights online. Similarly, conditional reward modeling [6] allows a single reward model to flexibly apply different principles depending on context in training their evaluator LLM. These works highlight growing recognition that LLM alignment requires balancing diverse objectives which is closely related to our focus on dynamically eliciting new rubrics.

Evaluating and Training with Rubrics Recent work has extended the concept of verifiable rewards from domains like math and coding to more open-ended tasks by using rubrics for structured evaluation. This rubric-based approach has been adopted in various benchmarks for both expert [3, 34] and generalist domains [11]. Beyond evaluation, rubrics are now increasingly used as direct reward signals for reinforcement learning. Using structured rubrics as a direct reward has proven effective in both expert reasoning [16] and generalist alignment [37]. A diverse set of rubrics has also been used to train a single, robust reward model that generalizes across various domains [2]. Our work complements these methods; instead of using a static rubric or training a rubric-agnostic model, OnlineRubrics dynamically augments criteria online to adapt to the policy’s emergent behaviors.

3. Background

Rubrics are often used as drop-in replacement for rewards in any policy gradient learning algorithm.

3.1 Training Setup

In this work, we used the GRPO algorithm [33] maximizing the following objective

$$\mathcal{L}_{\text{GRPO}}(\theta) = \mathbb{E}_{i \sim \mathcal{D}, j \sim \mathcal{G}_i} \left[\min \left(r_{i,j}(\theta) \hat{A}_{i,j}^{\text{group}}, \text{clip}(r_{i,j}(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_{i,j}^{\text{group}} \right) - \beta \mathbb{D}_{\text{KL}}(\pi_{\theta} || \pi_{\text{ref}}) \right] \quad (1)$$

where $r_{i,j}(\theta) = \frac{\pi_{\theta}(o_{i,j}|x_i)}{\pi_{\theta_{\text{old}}}(o_{i,j}|x_i)}$ is the probability ratio, and advantages are calculated as normalized rewards:

$$\hat{A}_{i,j}^{\text{group}} = \frac{R_j - \text{mean}(\mathbf{R})}{\text{std}(\mathbf{R})} \quad (2)$$

where $\mathcal{D} = \{x_i, C_i\}$ is the set of training prompts and criteria, j indexes the output samples o_j from the group $o_j \sim \mathcal{G}_i$, $\pi_{\theta_{\text{old}}}$ is the policy before the update, π_{θ} the target policy. The rewards are computed independently for each o_j in the group and denoted by $\mathbf{R} = \{R_1, R_2, \dots, R_G\}$ where G is the group size.

In this work, we will assume that the true reward U can be modeled as a function of latent criteria and argue in Section 4.2 that for optimal modeling of the true reward all criteria should be elicited.

3.2 Rubric Based Rewards

In RLHF, reward signals in LLM training are traditionally modeled after human preferences with an explicit reward model in PPO [32] and GRPO or implicitly in DPO. In the case of queries where quick verification of the final answer is possible (i.e. numeric or short answer), exact match replaces human preferences for reward. More recently, rubrics for evaluating long-form answers are being used for calculating final scores [16, 19, 37] where an LLM-based grader (denoted by $\text{LLM}_{\text{grader}}$) evaluates a response against each criteria to compute R_j in Equation (3):

$$R_j = q\left(\text{LLM}_{\text{grader}}(o_j, x_i, C_i)\right) \quad (3)$$

Algorithm 1: Online Rubric Eliciting (OnlineRubrics)**Input:** Policy π_θ , control policy π_{control} , dataset $\mathcal{D}$, extraction prompt P_e , hyperparameter M **for** $\text{step} = 1, 2, \dots, N$ **do** Sample prompts and criteria $\{x_i, \mathcal{C}_i\}$ from $\mathcal{D}$; Update $\pi_{\text{old}} \leftarrow \pi_\theta$; Generate M candidate responses $\{o_{i,j}\}$ using π_{old} ; Generate M candidate responses $\{o_{i,j}^{\text{control}}\}$ using π_{control} ; Initialize $\mathcal{C}_i^e \leftarrow \emptyset$; **for** $k = 1, 2, \dots, M$ **do** Extract new criteria $\mathcal{C}_{i,k}^e \sim \text{LLM}_{\text{extract}}(x_i, o_{i,k}, o_{i,k}^{\text{control}}; P_e)$; $\mathcal{C}_i^e \leftarrow \mathcal{C}_i^e \cup \mathcal{C}_{i,k}^e$; De-duplicate $\mathcal{C}_i^e$; Compute rewards using Equation (3) and $\mathcal{C} = \mathcal{C}_i \cup \mathcal{C}_i^e$; Compute group advantages $\hat{A}_{i,j}$ Equation (2); Update θ via policy gradient by maximizing Equation (1)

where $\mathcal{C}_i = \{(c_1, w_1), (c_2, w_2), \dots, (c_d, w_d)\}$ is a collection of criteria with corresponding importance weights that describe an ideal response to the prompt, and q is an reduction function. The judge $\text{LLM}_{\text{grader}}$ [42] evaluates the output o_j against each criterion in $\mathcal{C}_i$ and produces a list of binary outcomes which are then reduced to a single scalar value by q using the weights, if applicable. In this work we implement the reduction function as a weighted sum of the grades normalized by the total possible maximum score:

$$q(x, o, \mathcal{C}) = \frac{w^\top \text{LLM}_{\text{grader}}(x, o, \mathcal{C})}{\sum_{k:w_k > 0} w_k} \quad (4)$$

where $\text{LLM}_{\text{grader}}(x, o, \mathcal{C}) \in \{0, 1\}^d$ is the binary grades corresponding to each criterion.

4. Online Rubric Elicitation

Rubric-based reward calculation provides richer feedback than reward-model-based post-training, yet it fails to mitigate the problems that might emerge during policy gradient updates. Specifically, we observe that initial rubrics tend to represent the desired qualities of an ideal response while putting less emphasis on describing undesired qualities. For example, when the prompt is “How can I test for the presence of carbon dioxide in a reaction?” and the rubric is (+9, *The response mentions limewater turning milky*), both responses “Bubble the gas through limewater; it turns milky due to calcium carbonate formation. This reaction is specific to CO₂” and “Bubble the gas through limewater; it turns milky due to calcium carbonate formation, which is slightly soluble in acidic conditions” receive the full score, while the latter includes technically accurate but unnecessary information unrelated to the prompt. Such mishaps may only be detected as they arise during rollouts. Moreover, emerging desirable qualities (e.g., “This reaction is specific to CO₂”) that are not currently rewarded by the existing rubric set will be overlooked by the algorithm.

We propose a novel method called OnlineRubrics that leverages pairwise comparison of candidate responses to derive novel criteria—OnlineRubrics is designed to capture potential errors and identify useful features. The approach simply augments the set of offline criteria i.e. the portion of the rubric that is created a priori for the specific prompt, with more criteria derived during the training. Our approach is different from recent work that uses a fixed set of criteria (or checklists) [2] for multiple data points or other procedures to extract rubrics in a pointwise manner by simply considering a prompt [19]. OnlineRubrics drives insights from the pairwise reward modeling literature [5, 27, 36].

4.1 LLM-based Criteria Elicitation

OnlineRubrics begins with an initial set of *offline criteria* $\mathcal{C}_i$ that may be provided by human annotators or created synthetically. During policy training, at step t before any updates, given a prompt x_i we sample a set of candidate responses from a *control* policy (e.g. the initial policy, π_{ref} , or the policy from the previous step π_{old}) and the

You are given a prompt and pair of responses to the same prompt. Your task is to **identify their differences not already covered by the existing rubrics**. [truncated] First, analyze both responses to identify the differences. Then, transform these observations into new evaluation criteria if they're not already covered by existing rubrics. This is very important: any rubric that you introduce should be **based on one of the responses**. Do not use your own knowledge to introduce new criteria that are not based on one of the responses.

Focus on criteria that distinguish genuinely helpful responses from those gaming the system. [truncated] Assign a positive weight (integer) to each of the new criteria based on the relative importance of the criterion to the existing criteria. If no meaningful new criteria are needed, return an empty list.

```
{{Existing Rubric}}
{{Response A}}
{{Response B}}
```

Figure 2: Abbreviated system prompt template used for eliciting new criteria from pairwise response comparisons, see full prompt in Figure 8.

current policy π_θ^t . We define an LLM-based rubric extractor $\text{LLM}_{\text{extractor}}$ conditioned on the system prompt P_e (see Figure 2) whose task is to identify the differences between a pair of responses ($o_{i,j}, o_{i,j}^{\text{control}}$) sampled from the current and control policies, respectively, and turn them into useful criteria and corresponding weights. We repeat this procedure independently for each prompt in the batch and augment their corresponding rubrics with the new criteria before the policy parameter update. We provide the procedure in Algorithm 1.

We adopt a two-step approach for criteria elicitation; in the first step, we ask $\text{LLM}_{\text{extractor}}$ to enumerate the meaningful differences between a pair of responses with references to where these differences arise in the responses. In the second stage, we reduce the criteria that are duplicates or overlap significantly to avoid redundancy following our desiderata in Section 5. The system prompt template used to extract rubrics is given in Figure 2 and the deduplication prompt is available in Figure 9. By default, we compare eight pairs of rollouts from each of the control and current policies and extract about eight criteria at the end of the procedure.

OnlineRubrics Variants We experiment with two variants depending on the source of alternative responses π_{control} among π_{ref} or π_{old} . We empirically observe in Table 2 that sampling the control set of responses from the π_{old} also performs quite strongly compared to the setting $\pi_{\text{control}} = \pi_{\text{ref}}$ if not better.

4.2 A Formal Motivation for OnlineRubrics

Let f be the grades from $\text{LLM}_{\text{grader}}$ for the prompt, response and criteria triplet $(x, o, \mathcal{C})$ such that $f(x, o, \mathcal{C}) \in \{0, 1\}^d$ where $\mathcal{C}$ and w are the set of criteria and weights and d is the size of the criteria. Let also $\mathcal{C}^E$ (explicit) and $\mathcal{C}^I$ (implicit) to denote to the set of criteria in the rubric and those not in the rubric, respectively, and $f_E(x, o)$ to indicate the binary grades for the output o under criteria $\mathcal{C}^E$.

Proposition 1. Suppose that

- $\mathcal{C}^*$ is the set of true criteria. f_* can be split into $f_* = (f_E, f_I)$ and $\mathcal{C}^* = (\mathcal{C}^E, \mathcal{C}^I)$.
- The true reward is $U(x, o) = w_E^\top f_E(x, o, \mathcal{C}^E) + w_I^\top f_I(x, o, \mathcal{C}^I)$ and the estimated reward $R_t(x, o) = w_E^\top f_E(x, o)$ at step t .
- Assuming GRPO style updates, the gradient under the true reward then would be $g_U = \mathbb{E}[\nabla_\theta \log \pi_\theta(o|x) U(x, o)]$ and the estimated gradient $g_{R_t} = \mathbb{E}[\nabla_\theta \log \pi_\theta(o|x) R_t(x, o)]$

Then,

$$\|g_U - g_{R_t}\|_2 \leq \sqrt{\mathbb{E}[\|\nabla_\theta \log \pi_\theta\|^2]} \|w_I\|_1$$

Proposition 1 shows that the difference between the gradient steps is upper-bounded by $\|w_I\|_1$ times the expected squared norm of the policy score function. Augmenting the rubric to better approximate the true criterion set leads to better estimation of the true gradient hence improved stability and sample efficiency during training. That said,

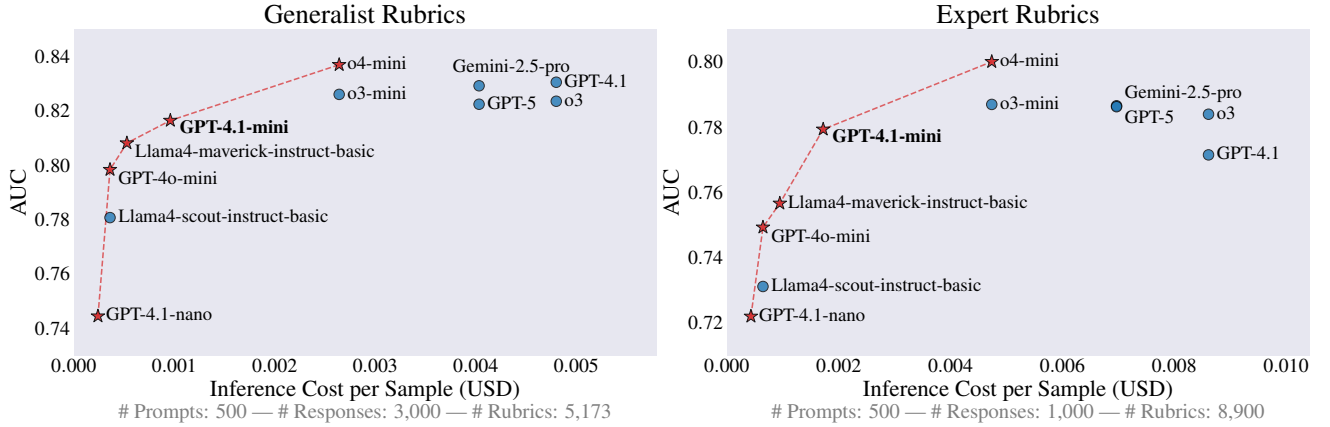


Figure 3: Performance of different LLM graders. AUC score is calculated using the receiver operating characteristic (ROC) curve. The best grader is the one with the highest AUC score and the lowest inference cost per sample. Models on the Pareto frontier (shown as a red dotted line) are the best trade-off between the two metrics. We choose GPT-4.1-mini as our default grader, balancing alignment quality with inference cost.

OnlineRubrics should be viewed as a step toward tightening the upper bound on the implicit, unmodeled mass $\|w_I\|_1$, rather than a complete recovery of the true criteria set. Proof is given in Appendix A.

5. Datasets

We trained OnlineRubrics with two collected rubric datasets: Generalist Rubrics and Expert Rubrics. Generalist Rubrics consists of real-world, single-turn prompts contributed with user consent and curated to be safe, rubric-eligible, and generalist in scope. For each prompt, human annotators authored a prompt-specific rubric composed of weighted, binary-checkable criteria.

Expert Rubrics extends the same rubric framework to expert-authored problem sets across Physics, Chemistry, Biology, and Math. Each task bundles a prompt, an expert grading rubric with binary-evaluable and weighted criteria, sample model responses, and detailed rubric ratings.

We use a subset of both datasets as evaluation sets and exclude from training. Table 1 shows the statistics of the datasets. On average, Generalist set contains 10.4 rubrics per sample and Expert set contains 18.0 rubrics per sample.

Across both datasets, rubrics are human-written and follow the same annotation principles: criteria are *Mutually Exclusive & Collectively Exhaustive*, *Atomic*, *Objective*, and *Self-Contained*; ensuring they can be verified reliably and used as dense reward signals in offline and online training. See Appendix B for data samples.

We evaluate OnlineRubrics on (1) evaluation sets of both datasets by calculating rubrics score and win rate using Gemini 2.5 Pro [9] as an LLM-Judge, and (2) on the following public benchmarks: GPQA-Diamond [30], GSM8K [8], AlpacaEval [12, 22], and Arena-Hard [20, 21].

6. Experiments and Results

We begin by identifying the most effective LLM-based grader for rubric grading in Section 6.1. Next, we introduce our baselines in Section 6.2 and report the main results with OnlineRubrics in Section 6.3. Finally, we perform a qualitative analysis of the elicited rubrics in Section 6.4.

Table 1: Generalist and Expert Rubrics datasets statistics.

	Train		Eval.	
	# Sam.	# Rub.	# Sam.	# Rub.
Generalist	1,500	15,528	487	5,003
Expert	1,864	33,554	332	5,938
Math	584	9,512	104	1,688
Biology	506	9,863	90	1,750
Physics	314	5,631	56	1,001
Chemistry	460	8,548	82	1,499

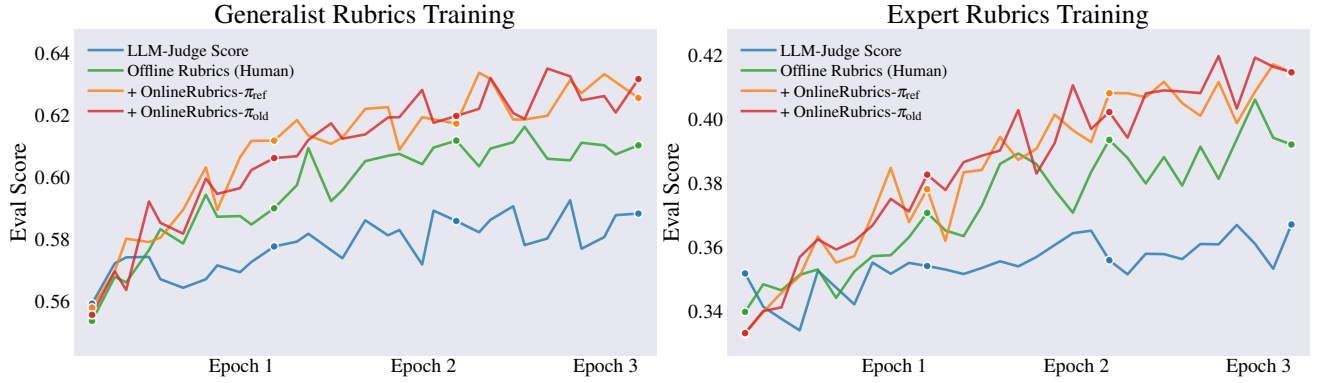


Figure 4: Results on the evaluation set of the Generalist and Expert datasets during training (higher is better). The evaluation set is fixed and does not contain any elicited rubrics. Both OnlineRubrics methods outperform using Offline Rubrics (Human) or LLM-judge Score (a Likert scale).

We train Qwen-2.5-7B-Instruct [28] with GRPO as the training algorithm on the training data from both Generalist and Expert Rubrics datasets for 3 epochs and evaluate on the eval set of the respective datasets 10 times during each epoch. We use *o3-mini* as the $LLM_{extractor}$ and set the number of pairwise comparisons to 8. Appendix C provides the detailed experimental settings.

6.1 Verifier Selection

Rubrics training requires an LLM grader to evaluate whether an output o_j meets the criteria specified in the rubrics C_i . The input to the grader is a (prompt x_i , output o_j , rubrics C_i) triplet, and the output is a sequence of binary scores indicating whether each criterion $c_k \in C_i$ is satisfied by the output. Although grading is assumed to be easier than generation [35], it is still a challenging task for LLMs and remains under-explored in previous work on rubrics due to the lack of human-annotated data with fine-grained rubric-level scores. However, different LLM graders have different evaluation capabilities, which can significantly affect the training of rubrics-based models. To address this, we have collected human evaluations of the original human-written rubrics for 2-6 sampled responses per prompt for 500 prompts for each of Expert and Generalist sets.

Using this dataset, we evaluate the performance of several LLM graders and present the results in Figure 3. Given that during the rubrics-based training, we need to evaluate multiple rollouts for each prompt, it is important to choose a grader with a low inference cost per sample. We calculate the inference cost per sample by dividing the total inference cost by the total number of samples.

Perhaps unsurprisingly, we find that all verifiers perform better on the Generalist dataset than the Expert dataset (average AUC score of 0.811 vs 0.768). Interestingly, the Pareto frontier for the Generalist dataset is the same as the Pareto frontier for the Expert dataset. This suggests that the relative performance of the verifiers is not affected by the domain. We choose GPT-4.1-mini as our default grader, balancing the alignment with grades with inference costs.

6.2 Baselines

We compare our methods with the following baselines:

LLM-Judge Score We train the model by only using an LLM-judge to grade the responses on a Likert scale without any rubrics. The input to the LLM-judge is a prompt-response pair (x_i, o_j) , and the output is a Likert score that is converted to a reward $R_{i,j}$ using a linear mapping. We experiment with *o3-mini* as the LLM-judge. The prompt is given in Appendix D.

Offline Rubrics (Synthetic) We use the same prompts available in the Generalist and Expert Rubrics datasets. However, instead of using human-written rubrics, we synthetically create rubrics using *o3-mini*. See the prompt in Appendix D.

Offline Rubrics (Human) We train the model with human-written rubrics from the Generalist and Professional

Model	Generalist Rub.		Alpaca-Eval		Arena-Hard
	Score	WR	WR	LC-WR	WR
<i>Baselines</i>					
Qwen-2.5-7B-Instruct	55.4	39.0	30.0	28.2	50.0
+ LLM-Judge Score	58.8	51.3	42.2	26.9	51.0
+ Offline Rubrics (Synthetic)	58.8	52.8	39.5	28.2	51.5
+ Offline Rubrics (Human-written)	61.0	62.2	46.4	28.0	52.4
+ Universal Requirements	59.4	59.1	44.4	30.3	53.8
+ Pointwise Extraction	<u>62.9</u>	64.9	48.1	29.4	51.1
<i>Our Methods</i>					
+ OnlineRubrics- π_{ref}	62.7	<u>67.6</u>	<u>54.0</u>	31.5	<u>55.7</u>
+ OnlineRubrics- π_{old}	63.2	68.2	55.0	<u>30.4</u>	56.5

Table 2: Results on the instruction-following benchmarks. WR stands for Win Rate and LC-WR is Length-Controlled Win Rate. We highlight the best performing model in each column in bold and underscore the second best performing approach. Both OnlineRubrics methods (OnlineRubrics- π_{ref} and OnlineRubrics- π_{old}) are consistently better than the baselines except for one case.

Model	Expert Rub.		GPQA-D	GSM8K
	Score	WR	Acc.	Acc.
<i>Baselines</i>				
Qwen-2.5-7B-Instruct	33.6	31.9	34.7	79.2
+ LLM-Judge Score	36.7	44.0	34.5	79.1
+ Offline Rubrics (Synthetic)	37.1	46.4	36.6	79.2
+ Offline Rubrics (Human-written)	39.2	51.8	36.2	79.9
+ Universal Requirements	39.7	53.3	36.6	<u>80.1</u>
+ Pointwise Extraction	40.9	<u>57.1</u>	33.6	78.3
<i>Our Methods</i>				
+ OnlineRubrics- π_{ref}	<u>41.4</u>	61.0	<u>37.6</u>	80.0
+ OnlineRubrics- π_{old}	41.5	56.5	38.1	80.5

Table 3: Results on training on the Expert rubrics. WR stands for win rate and Acc. stands for accuracy. We highlight the best performing model in each column in bold and underscore the second best performing approach. Both OnlineRubrics methods outperform the baselines.

Rubrics datasets. As we shall see, using human-written rubrics, often significantly, is better than using synthetic rubrics across the benchmarks we evaluate.

Universal Requirements As discussed in Section 2, previous work argued that adding a fixed set of criteria to all samples helps the model to make training more stable and prevent reward hacking. We use the same universal requirements as in Viswanathan et al. [37] and show OnlineRubrics, which elicits sample-grounded rubrics online, outperforms these universal requirements.

Point-wise Elicitation In order to show the effectiveness of pairwise comparison, we also extract rubrics point-wise using the same extractor model. The input to the extractor is prompt x_i , a response o_j from the reference policy, and existing rubrics C_i . The output is a set of criteria C_i^e that we add to the human-written rubrics C_i .

6.3 Results and Discussion

Figure 4 shows the training curves for the Generalist and Expert datasets. Training with rubrics consistently scores higher and is more sample efficient than using LLM-Judge scores. More interestingly, adding the elicited rubrics during training (OnlineRubrics) improves the performance of the model on the evaluation sets of both datasets, which only contain human-written rubrics.

Table 2 and Table 3 present the results on a set of instruction-following and reasoning benchmarks, respectively. Training with Offline Rubrics (Human) is improving the performance of the model on all the respective datasets with the only exception being length controlled win rate on AlpacaEval (28.2% vs 26.9%). Importantly, training with Offline Rubrics (Human) is (a) always better than using LLM-Judge scores across all benchmarks, and (b) is better than using synthetic rubrics across 7 out of 9 evaluation metrics. More interestingly, adding the elicited rubrics to the offline rubrics (human-written) during training (OnlineRubrics) further boosts performance across both instruction-following and reasoning benchmarks. On AlpacaEval, for instance, OnlineRubrics- π_{ref} increases the win rate from 46.4% to 55.0%, while also improving the length-controlled win rate (LC-WR) from 28.0% to 31.5% reflecting better quality responses in general.

When compared against other baselines, OnlineRubrics is consistently better than Universal Requirements across all benchmarks. This is interesting because it suggests that sample-grounded elicited rubrics are more effective than augmenting the rubrics with a set of fixed criteria that fail to capture the nuances of individual prompts and remain static as the policy evolves during training. While adding pointwise extracted rubrics also often improves over offline rubrics, it is still surpassed by OnlineRubrics (48.1 vs. 54.0 and 55.0 on AlpacaEval, 51.1 vs. 55.7 and 56.5 on Arena-Hard). OnlineRubrics leverage pairwise differences to highlight discriminative properties that distinguish a better response from a worse one rather than relying on a single response.

6.4 Qualitative Analysis

We conduct a qualitative analysis of the elicited criteria and contrasted it with human-written rubrics. In summarizing the differences, we apply an LLM-based comparison of rubric updates (between the initial rubrics and rubrics at the last epoch) followed by clustering to identify recurring themes. We observe several consistent types of improvements in elicited criteria emerge. First, elicited criteria frequently introduced *evidence grounding* (e.g., *The response includes only categorically relevant, evidence-backed details.*), *reproducibility* (e.g., *The response avoids any process that can't be reproduced without modern technology.*), and *holistic anti-gaming criteria* (e.g., *The response avoids over-specification and over-enumeration.*), broadening the evaluative focus beyond surface-level correctness. Second, many criteria emphasize *practicality and real-world feasibility* rewarding implementation readiness and resource awareness. Third, we observe that the addition of meta-criteria such as *structural organization*, *causal reasoning*, and *uncertainty handling* enhance the rubric's coverage of system-level and methodological dimensions.

Overall, the new criteria highlight that online elicitation tends to expand and strengthen rubrics over time. Instead of remaining fixed, criteria adapt dynamically as new errors or weaknesses are exposed, leading to more comprehensive and resilient evaluation standards. A complete list of clusters with proportions is presented in Appendix E.

7. Conclusion

We have described OnlineRubrics, a framework for dynamically eliciting new criteria from pairwise comparisons of responses during reinforcement learning. Unlike static rubrics which may be incomplete or become obsolete as training progresses, our approach aims to continuously surface overlooked errors or emerging desired properties. This yields robust gains across expert and generalist domains. Our results show improvements of up to 8 percentage points over training exclusively with human-written rubrics on AlpacaEval, GPQA and Arena-Hard. By moving rubric elicitation online, OnlineRubrics adapts as training evolves, capturing emergent behaviors and strengthening alignment beyond what fixed rubrics allow.

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A. Proof for Proposition 1

Proof.

$$\begin{aligned}
 g_U - g_{R_t} &= \mathbb{E}_{(x,o)} \left[\nabla_{\theta} \log \pi_{\theta}(o|x) (U - R_t) \right] \\
 &= \mathbb{E}_{(x,o)} \left[\nabla_{\theta} \log \pi_{\theta}(o|x) (Y - \mathbb{E}_{(x,o)}[Y]) \right] \quad \text{where } Y = U - R_t
 \end{aligned}$$

because $\mathbb{E}_{(x,\rho)}[\nabla_{\theta} \log \pi_{\theta}(o|x)] = 0$ we can center Y without changing the expectation. Then

$$\begin{aligned}
\|g_U - g_{R_t}\|_2 &= \left\| \mathbb{E}_{(x,\rho)} \left[\nabla_{\theta} \log \pi_{\theta}(o|x) (Y - \mathbb{E}_{(x,\rho)}[Y]) \right] \right\|_2 \\
&\leq \sqrt{\mathbb{E}[\|\nabla_{\theta} \log_{\pi_{\theta}}\|^2]} \sqrt{\text{Var}(Y)} \quad \text{by Cauchy-Schwarz} \\
&= \sqrt{\mathbb{E}[\|\nabla_{\theta} \log_{\pi_{\theta}}\|^2]} \sqrt{\text{Var}(U - R_t)} \\
&= \sqrt{\mathbb{E}[\|\nabla_{\theta} \log_{\pi_{\theta}}\|^2]} \sqrt{\mathbb{E}[(U - R_t)^2]} \\
&= \sqrt{\mathbb{E}[\|\nabla_{\theta} \log_{\pi_{\theta}}\|^2]} \|w_I\|_1
\end{aligned}$$

□

B. Data Samples

We provide two samples showing sampled rollouts from current and reference policies, along with human and elicited rubrics in Figures 5 and 6. Each criteria are preceded with its importance weight which range between 1-5 for Generalist and -10 and 10 for Expert sets.

C. Experimental Settings

C.1 Training Settings.

We train Qwen-2.5-7B-Instruct [28] on the training set of the Generalist and Expert Rubrics datasets for three epochs. Training follows the GRPO procedure described in Section 3, with 16 rollouts generated per sample. We use GPT-4.1-mini as the LLM_{grader} and o3-mini as the LLM_{extractor}, performing eight pairwise comparisons per instance. Optimization uses a learning rate of $5e-6$ with a warmup ratio of 0.1. KL-divergence regularization is applied with a coefficient of 0.01. All experiments are conducted on 8 NVIDIA H100 GPUs with per-device batch size of 6 and gradient accumulation of 2 steps (effective batch size is 96).

C.2 Evaluation Settings.

Generalist and Expert Rubrics Datasets. We calculate the score and win rate (vs. the reference policy) on the evaluation set of the Generalist and Expert Rubrics datasets. Score is calculated as explained in Equation (4). We use GPT-4.1-mini as the LLM_{grader}. We use Gemini-2.5-Pro as the LLM-Judge that picks the winner between the two responses. For each sample, we run the judge twice by flipping the order of the two responses. If the judge picks the same response twice, we consider it as a win. The prompt for the judge is given in Appendix D.

AlpacaEval. We use the evaluation script¹ from [22] to calculate the win rate and length controlled win rate on the evaluation set of AlpacaEval using the default settings.

Arena-Hard. We use the evaluation script² from [20, 21] to calculate the win rate (vs. the reference policy) on the evaluation set of Arena-Hard. We use GPT-4.1 as the LLM-Judge.

GPQA-Diamond. We use simple-evals³ for evaluation on GPQA-Diamond [30] and report the average accuracy across 4 runs.

GSM8K. We use lm-evaluation harness Gao et al. [14] to calculate the strict match accuracy on the evaluation set of GSM8K [8].

¹https://github.com/tatsu-lab/alpaca_eval

²<https://github.com/lmarena/arena-hard-auto>

³<https://github.com/openai/simple-evals>

Prompt:

Tell me the easiest way to analyze dozens of different PDFs from different hotels and organize their rates on Google Sheets.

Offline Rubrics (human)

5.00	The response must recommend using a PDF conversion/extraction tool to create a CSV or Excel file, such as SmallPDF, Tabula, Adobe Acrobat, PDFTables, etc.
5.00	The response must provide example header terms such as "hotel name," "rate," "room type," "additional fees," etc., for the Google Sheet tables.
1.00	The response should clarify whether a software service is free or may require paid subscriptions to use their extraction, conversion, or programming functions.
5.00	The response should recommend ways to analyze the data, such as inserting pivot tables or creating charts/graphs from the data in Google Sheets.
1.00	The response should use emboldened headers to differentiate sections of the text.
1.00	The response should provide an example prompt to input for using an AI tool.
3.00	The response should provide recommendations on how to clean up the data, such as searching and deleting duplicate entries, formatting currency consistently, etc.
5.00	The response must explain how to use the "Import" and/or "Query" functions in Google Sheets to import the CSV or Excel files into the Sheets file.
5.00	The response must explain how to copy and paste data manually from the outside files into the Google Sheets file.
1.00	The response should recommend storing files in accessible locations, such as named folders.
5.00	The response should recommend Optical Character Recognition (OCR) programs like Adobe Acrobat, Google Drive, or Tesseract OCR, in case the PDFs are scanned images rather than searchable text.
3.00	The response should recommend using Generative AI programs like ChatGPT to extract the necessary information from the PDF files into a table or CSV.
3.00	The response should recommend coding using Python, JavaScript, Google Script, etc., as an extra way to combine the PDFs into a Google Sheet or automate repetitive tasks in the conversion process.
1.00	The response should provide an example code to illustrate how to convert or automate the task related to its coding recommendation.
3.00	The response should provide a step-by-step guide for all of the methods that it recommends, formatted as a numbered list.

OnlineRubrics- π_{ref}

4.00	The response should present multiple alternative approaches—including manual, semi-automated, and automated (coding-based vs. web-tool based) methods—that cater to different user technical skills and PDF complexities, clearly outlining pros, cons, prerequisites, and decision criteria for selecting a method.
3.00	The response should include error handling, data validation, and troubleshooting guidance to ensure robustness and accuracy throughout the data extraction and conversion process.
2.00	The response should provide detailed, actionable setup instructions, such as dependency installation and environment preparation, to ensure smooth replication of the automation process.
3.00	The response should include sustainable data management practices and long-term maintenance recommendations—such as regular backups, documentation, routine validation, and update notifications—to ensure the solution remains effective over time.
4.00	The response should comprehensively integrate multiple tool options and methodologies (e.g., OCR, add-ons, programming scripts, advanced automation) tailored to the specific characteristics of the PDFs, and provide contextual decision guidance along with rational justifications for each recommended tool.
3.00	The response should include explicit instructions for managing API credentials and safeguarding sensitive data, including secure handling of API keys and credentials when using online services or APIs.
5.00	The response should strike a balance between detailed technical instructions (including code examples) and high-level guidance to be accessible to both technical and non-technical users.
3.00	The response should include clear, practical, and well-commented code examples with detailed explanations that are realistic, adaptable, and genuinely instructive.
4.00	The response should demonstrate comprehensive integration of data extraction with subsequent data organization, elaborating on how the automation seamlessly flows from extraction to updating Google Sheets.
2.00	The response should maintain instructional coherence by sequencing steps logically so that each step builds on the previous one and is clearly connected to the overall objective.
3.00	The response should include explicit warnings and instructions for safely customizing and testing code examples, such as alerting users to replace placeholders and to test scripts on a subset before bulk execution.

OnlineRubrics- π_{old}

4.00	The response should clearly differentiate between manual extraction methods and automated processes, providing guidance for users of varying technical expertise and indicating the appropriate context for each approach.
4.00	The response should provide practical, well-explained, and executable code examples that use accessible and well-documented APIs, are free of errors, and include guidance on error handling, testing, and debugging.
3.00	The response should include a clear and organized prerequisites/setup section that outlines the necessary tools, file organization steps, and initial conditions before commencing the main procedure.
3.00	The response should include clear recommendations for data integrity, including guidance on error handling, validation, backup strategies, and verification of assumptions about data consistency and structure.
3.00	The response should strike an effective balance between technical detail and user-friendly, step-by-step instructions that guide non-expert users through the entire process.
5.00	The response must maintain consistent language throughout and avoid switching to non-requested languages that could confuse users.
5.00	The response must remain fully focused on the user prompt, avoiding extraneous or unrelated content that does not contribute to solving the stated problem.
3.00	The response should offer a coherent and integrated explanation that clearly connects the PDF extraction process with the Google Sheets update.
2.00	The response should offer robust fallback strategies, including manual extraction methods, in case automated extraction tools fail due to variations in PDF formats.
3.00	The response should avoid over-engineering by including only the most relevant and practical information, rather than an overabundance of optional methods and excessive technical detail.

Figure 5: Data sample from the Generalist Rubrics dataset.

D. System Prompt Templates

Figures 8 and 9 show the system prompt templates used for $LLM_{extractor}$ and de-duplicating extracted criteria, respectively. We use the system prompt provided in Figure 10 for LLM_{grader} .

Figures 11 and 12 show the system prompt templates used for LLM-Judge Score and LLM-Judge for win rates, respectively. We use the system prompt provided in Figure 13 to generate synthetic offline rubrics.

E. Qualitative Rubric Clusters

We report the clusters of rubric refinements observed during online elicitation. Figure 7 lists each cluster with its name, a concise description, and its share of samples, sorted by proportion.

Prompt:

I have glyoxal in my lab and I want to use it to prepare 1,1,4,4-tetramethylcyclohexane. Show me an economical plan for this synthesis and identify any hazards.

Offline Rubrics (human)

- 5.00 The response must include glyoxal as the starting material.
- 5.00 The product of the synthesis plan must be 1,1,4,4-tetramethylcyclohexane.
- 5.00 The plan includes a valid step to form a diene, such as Wittig reaction and elimination reaction.
- 5.00 The plan includes a valid step to form a 6-member ring structure, such as Diels-Alder reaction and pinacol coupling reaction.
- 5.00 The plan includes a valid step to hydrogenate the 6-member ring, such as hydrogenation with Raney-Ni as catalyst.
- 2.00 The response gives consideration of alternative routes, such as Wittig reaction to create a diene.
- 5.00 The response claims aldol condensation for glyoxal.
- 5.00 The response claims two methyl groups added by sufficient Grignard reagent on a ketone carbonyl.
- 5.00 The response claims only one double bond formed by elimination of diol.
- 10.00 The response claims geometrically impossible organic structure, such as 2,2-dimethyl-ethanedial.
- 8.00 The response claims formation of a 6-member ring starting from insufficient carbon in the pinacol coupling reaction.
- 2.00 The response includes suggestions to manage hazards, such as waste disposal instructions.
- 5.00 The plan must identify hazards of each step, such as toxicity, and flammability of materials.
- 3.00 The response must present the plan in a clear format with bolded sections titles.
- 3.00 The synthesis should have less than 5 major steps for economic consideration.
- 2.00 The plan includes tips to efficiently execute the plan, such as trial experiments with minimum amount.
- 2.00 The organic chemicals mentioned in the plan follows IUPAC nomenclature rules.
- 2.00 The plan uses expensive chemicals, such as reagents containing precious metals.
- 2.00 The plan includes discussions on the yield of each step for the economical aspect.
- 5.00 The plan includes a valid step to extend the carbon chain of glyoxal, such as Wittig reaction and Grignard reaction.

OnlineRubrics- π_{ref}

- 5.00 The response must provide a synthesis pathway that is mechanistically plausible and grounded in established organic reaction principles, with a clear, logical justification for each step and a differentiation between well-established and speculative reaction pathways.
- 4.00 The response should provide specific, precise, and quantitatively justified reaction details (e.g., yields, temperatures, reaction times) that reflect well-known reaction pathways and enhance clarity and reproducibility.
- 4.00 The response should present a clear, step-by-step experimental procedure with a logical progression of reaction conditions that support the synthesis mechanism.
- 4.00 The response must integrate hazard management into each experimental step by providing clear, stage-specific hazard identification—including specific chemical safety hazards—and actionable safety protocols tailored to each reaction phase.
- 3.00 Include explicit experimental reaction monitoring procedures to validate each reaction stage.
- 2.00 Provide a detailed product workup and purification strategy that explains how to isolate the target compound post-reaction.
- 3.00 The response must present its synthesis plan and safety discussions entirely in a consistent language without switching mid-response.
- 3.00 The response should be concise and focused, providing only the necessary reaction steps and hazard information directly relevant to the synthesis.
- 3.00 The synthesis plan should present at least one practical alternative pathway or modification that offers improved safety or cost-effectiveness without overcomplicating the core synthetic strategy.
- 3.00 The synthesis plan must integrate economic analysis that links reagent costs, potential reaction yields, and waste management, ensuring that economic recommendations are directly tied to specific reaction steps.
- 2.00 The response should include practical considerations for scale-up and process safety, indicating attention to experimental feasibility beyond bench-scale protocols.
- 4.00 The synthesis plan should directly use glyoxal as the starting material unless a significant economic or safety advantage, with strong justification, is provided for deviating from the specified reactant.
- 3.00 Chemical nomenclature and identity must be accurate, with synonyms and alternative names correctly reflecting the actual chemical structure.

OnlineRubrics- π_{old}

- 3.00 The response should maintain consistent language usage throughout and avoid switching languages abruptly unless justified by content.
- 5.00 The response should clearly and concisely list only those mechanisms that are directly relevant to NRF1-mediated protection in human 3xSNCA neurons, avoiding extraneous, tangential, or overly peripheral details.
- 5.00 The response should exhibit clear structural organization, using well-defined sections, subheadings, or bullet points to group related mechanisms and explicitly link each mechanism to its protective impact on human 3xSNCA neurons, including integration of experimental evidence, therapeutic implications, and future research directions where appropriate.
- 3.00 The response should synthesize complex mechanistic interactions and balance depth with relevance, ensuring that elaborated mechanisms directly support the core question of NRF1-mediated protection in 3xSNCA neurons without diverging into tangential details.
- 3.00 The response should provide detailed mechanistic nuance by clearly linking NRF1 overexpression to specific neuroprotective pathways, including aspects of mitochondrial biogenesis, redox processes, and the interface with neuronal survival pathways.
- 2.00 The response should include evidence or translational context that connects mechanistic details with potential experimental or clinical outcomes in human 3xSNCA neurons.

Figure 6: Data sample from the Expert Rubrics dataset.

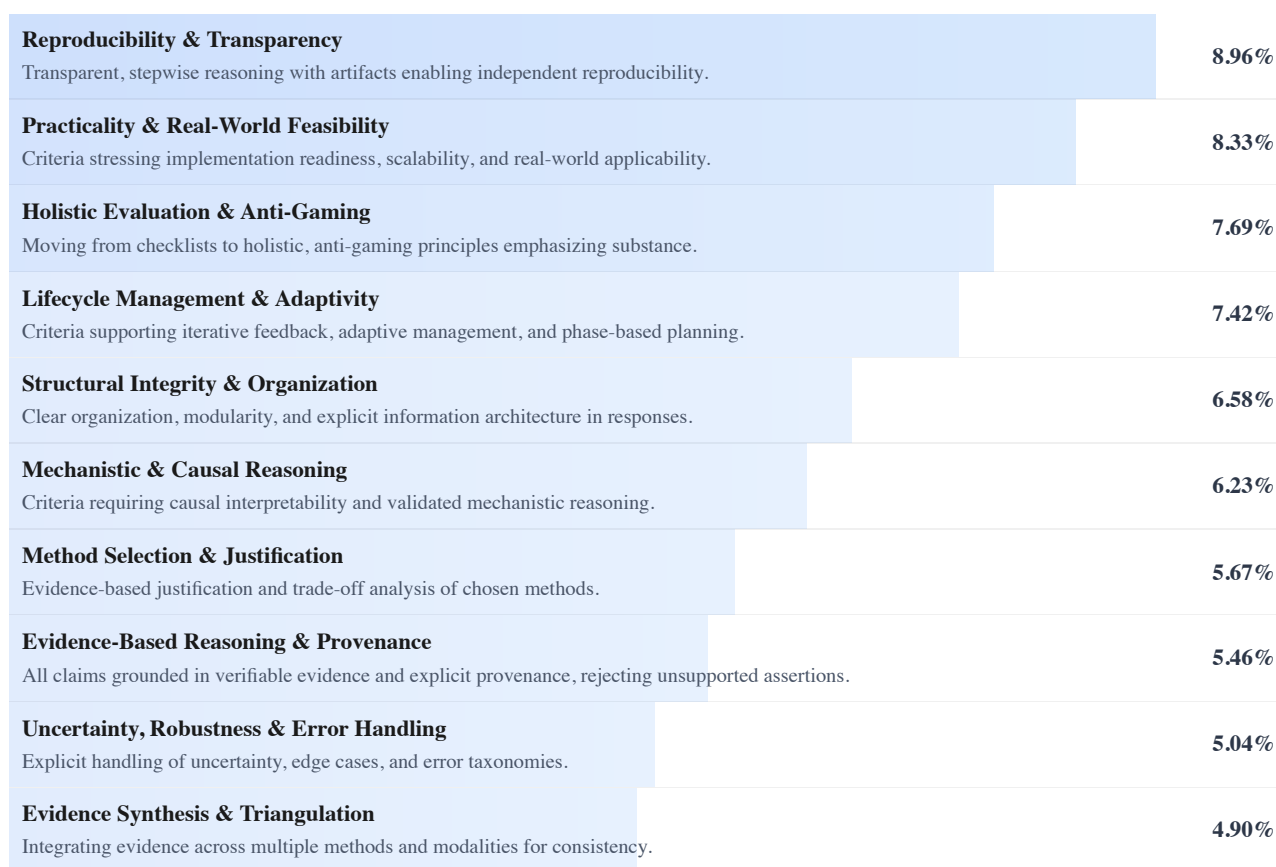


Figure 7: Top-10 most frequent clusters of rubric criteria elicited via OnlineRubrics. Each cluster is shown with a short description and its share of samples, sorted by proportion.

You are given a prompt and pair of responses to the same prompt. One of the responses is from a trained model and the other is from a baseline model.

Both responses are evaluated using an existing rubric. Your task is to identify their differences not already covered by the existing rubrics.

You should find the properties of one response that are better than the other.

Also, try to identify reward hacking patterns in the responses.

Reward hacking is a pattern where the response achieves a high score on rubrics by exploiting a loophole in the rubrics. Think of reward hacking as a way to game the rubrics to get a high score. Reward hacking is like following the letter of the law but not the spirit of the law.

First, analyze both responses to identify the differences. Then, transform these observations into new evaluation criteria if they're not already covered by existing rubrics.

This is very important, any rubric that you introduce should be based on one of the responses.

Do not use your own knowledge to introduce new criteria that are not based on one of the responses.

Focus on criteria that distinguish genuinely helpful responses from those gaming the system. Also, keep an eye out for language switching patterns that might confuse the verifier.

Make sure the new criteria follow the same style as the existing criteria.

Assign a positive weight (integer) to each of the new criteria based on the relative importance of the criterion to the existing criteria.

Output format:

```
```json
{
 "analysis": "Your analysis of reward hacking patterns in the responses and good/bad behaviors that should be encouraged/discouraged. It's okay for the analysis to be long.",
 "new_criteria": [
 {
 "quote": "quote from the response following/violating the criterion",
 "criterion": "criterion_text",
 "weight": criterion_weight
 }
]
}
```
```

If no meaningful new criteria are needed, output:

```
```json
{
 "analysis": "Your analysis...",
 "new_criteria": []
}
```
```

Figure 8: Full system prompt template used for LLM_{extractor}.

You will review a collection of candidate evaluation criteria from multiple response comparisons and remove redundancy while preserving the best unique criteria. Your goal is ONLY to deduplicate and aggregate, NOT to introduce new criteria or remove criteria entirely.

Your Task: Deduplication and Aggregation ONLY

You should:

- **Remove redundant/overlapping criteria** that say essentially the same thing
- **Merge similar criteria** by combining them into a single, clearer criterion
- **Aggregate weights** for merged criteria (e.g., if two similar criteria have weights 3.0 and 4.0, the merged criterion might get weight 3 or 4).
- **Preserve all unique criteria** that address different quality aspects
- **Keep the original wording** when possible, only clarifying when necessary

You should NOT:

- **Add completely new criteria** not present in the candidate list
- **Remove criteria entirely** unless they are truly redundant
- **Change the intent** of existing criteria
- **Introduce your own knowledge** beyond what's in the candidates

Deduplication Process

1. **Group similar criteria** - Identify candidates that address the same quality aspect
2. **Select best wording** - Choose the clearest, most specific wording from each group
3. **Aggregate weights** - Combine weights from merged criteria appropriately. Only use positive integers.
4. **Preserve unique criteria** - Keep all criteria that address different aspects
5. **Maintain quality focus** - Ensure the final set covers all important quality dimensions from candidates

CRITICAL: You MUST end your response with JSON

```
```json
{
 "analysis": "Your analysis of redundancy patterns and merging decisions...",
 "final_criteria": [
 {
 "criterion": "Deduplicated criterion text (merged from similar candidates)",
 "weight": criterion_weight
 }
]
}
```

If all criteria are unique (no deduplication needed), return all candidates:

```
```json
{
  "analysis": "No redundancy found, all criteria are unique...",
  "final_criteria": [
    {
      "criterion": "Original candidate criterion 1",
      "weight": criterion_weight
    },
    {
      "criterion": "Original candidate criterion 2",
      "weight": criterion_weight
    }
  ]
}
```

Figure 9: Full system prompt template used for de-duplicating extracted criteria.

You are an expert evaluator. Given a user prompt, a generated response, and a list of quality rubrics, please evaluate the response against EACH rubric.

For each rubric,

- Mark "PRESENT" if the criterion is satisfied, or "NOT_PRESENT" if it is not. For example, given the response "Apples are red", the rubric "Mentions apples" is PRESENT, "Does not mention strawberries" is also PRESENT since the response doesn't mention strawberries and "Mentions oranges" is NOT_PRESENT. Also, "Avoids mentioning strawberries" is PRESENT because the response doesn't mention strawberries. However, "Avoids mentioning apples" is NOT_PRESENT because the response mentions apples.
- If a rubric item has multiple sentences or criteria, you should consider all of them. If any of the criteria is not met, the answer should be NOT PRESENT. Only return PRESENT if all of the criteria are met.
- One important exception to the above bullet point is that if a rubric says "such as", "for example", or "including", the response does not have to include all of the examples listed to meet the criteria. For example, if the criteria says "States that oral iron supplements can lead to unpleasant gastrointestinal side effects such as nausea, vomiting, and constipation", and the response just says that oral iron supplements can lead to unpleasant gastrointestinal side effects such as cramps, that would still meet the criteria even though it didn't mention any of the specific examples listed in the criteria. That is, there are no partial credit for any of the criteria.

Start your response with a valid JSON object that starts with "```json" and ends with "```".

The keys must be the numbers of the rubrics provided and the values must be either "PRESENT" or "NOT_PRESENT" based on your evaluation. Ensure the JSON is valid and contains no extra text or explanations.

Example response:

```
```json
{
 "1": "PRESENT",
 "2": "NOT PRESENT",
 "3": "PRESENT"
}
```

Figure 10: Full system prompt template used for LLM<sub>grader</sub>.

You are an expert evaluator. Given a user prompt and a generated response, please rate the overall quality of the response on a scale of 1 to 10, where 1 is very poor and 10 is excellent.

Start your response with a valid JSON object that starts with "```json" and ends with "```".

The JSON object should contain a single key "rating" and the value should be an integer between 1 and 10.

Example response:

```
```json
{
  "rating": 8
}
```

Figure 11: Full system prompt template used for LLM-Judge Score.

Please act as an impartial judge and evaluate the quality of the responses provided by two AI assistants to the user question displayed below.

You should choose the assistant that follows the user's instructions and answers the user's question better.

Your evaluation should consider factors such as the helpfulness, relevance, accuracy, depth, creativity, and level of detail of their responses.

Begin your evaluation by comparing the two responses and provide a short explanation.

Avoid any position biases ... Do not allow the length of the responses to influence your decision.

After providing your explanation, output your final verdict by strictly following this format:

"[[A]]" if assistant A is better, "[[B]]" if assistant B is better, and "[[C]]" for a tie.

Figure 12: Full system prompt template used for LLM-Judge for win rates.

Your job is to generate a self-contained set of evaluation criteria (“rubrics”) for judging how good a response is to a given question.

Terminology:

- A prompt is a task description (question) that a user gives to a model.
- A response is a model's output when given the prompt.
- A rubric is a set of criteria that capture the elements of an ideal response given a prompt. The rubric will be used to evaluate the quality of a response to the prompt. Rubrics can cover aspects of a response such as, but not limited to, factual correctness, ideal-response characteristics, style, completeness, helpfulness, harmlessness, patient-centeredness, depth of reasoning, contextual relevance, and empathy.
- A criterion is a single item in a rubric.

A good rubric follows these principles:

- As a whole, the rubric should be Mutually Exclusive (avoid overlapping criteria) and Collectively Exhaustive (all requests of the prompt should be covered).
- Each item should test one idea. If an item tests for the presence of X and Y, it should be split into two items (unless no reasonable prompt would contain one without the other).
- Each item should be binary (have yes/no answers) and as objective as possible. :x: "Response is too verbose" → :white_check_mark: "Response is less than 500 words long"
- Each item should be self-contained and include sufficient detail so that an uninformed grader can verify it without external knowledge. E.g. :x: "Names a 2010 Nobel Prize winner" → :white_check_mark: "Identifies one of the following 2010 Nobel Prize winners: A, B, or C".
- Avoid criteria that doesn't allow for partial credit. E.g. :x: "Mentions 3 Nobel Prize winners A, B, and C" → Split into "Mentions Nobel Prize winner A", "Mentions Nobel Prize winner B", "Mentions Nobel Prize winner C". All these should be detailed enough so that an uninformed grader can verify them without external knowledge.

Also consider the following axes when helping the user to improve the rubric:

- Communication Quality: Response length, clarity, level of detail, vocabulary, and structure are well-matched to the user and situation.
- Instruction Following: Adheres to the user's directions for how to complete the task or how to format a response. Satisfies all user constraints and answers all questions.
- Accuracy: Includes only factually correct information. Information is supported by evidence or consensus and uncertainty is expressed when evidence is limited.
- Context Awareness: Responds appropriately given the user's context (e.g., user role, setting, resources) and seeks clarification when needed.
- Completeness: Addresses all parts of the query needed for a safe and helpful response. Even if accurate, a response that omits key steps or considerations can still result in low-quality advice or harm.

Your task is to generate criteria for a given prompt. Also, you should assign a weight to each criterion. Weights should be an integer between 1 and 10.

Your response should be a json object with the following format. Use the reasoning fields to think about the criteria and reason about it.

```
{
  "initial_reasoning": INITIAL_REASONING,
  "rubrics": [
    {
      "reasoning": REASONING,
      "criterion": CRITERION,
      "weight": WEIGHT,
    },
  ]
}
```

Figure 13: Full system prompt template used to generate synthetic rubrics.