GR-SAP: Generative Replay for Safety Alignment Preservation during Fine-Tuning

Anonymous ACL submission

Abstract

Recent studies show that the safety alignment of large language models (LLMs) can be easily compromised even by seemingly non-adversarial fine-tuning. To preserve safety alignment during fine-tuning, a widely used strategy is to jointly optimize safety and task objectives by mixing in the original alignment data, which is typically inaccessible even for open-weight LLMs. Inspired by generative replay in continual learning, we propose **G**enerative **R**eplay for **S**afety **A**lignment **P**reservation **(GR-SAP)**, a unified framework that synthesizes domain-specific alignment data from LLMs and integrate them during downstream adaption to preserve safety alignment. Theoretical and empirical analyses demonstrate this synthetic data serves as a reliable proxy for the original alignment data. Experiments across various models and downstream tasks show that GR-SAP substantially mitigates fine-tuning–induced safety degradation while maintaining comparable downstream performance.[1]

Warning: This paper contains explicit content.

1 Introduction

The rapid advancement of large language models (LLMs) necessitates rigorous safety protocols to mitigate unintended consequences and potential misuse (Kim et al., 2022; Bianchi et al., 2023; Grattafiori et al., 2024; Bai et al., 2022b; Shevlane et al., 2023; Zou et al., 2023). Safety alignment aims to align LLMs' behavior with the "helpful and harmless" criteria (Bai et al., 2022a), which are typically integrated during the instruction-tuning stage (Ganguli et al., 2022; Song et al., 2024; Dai et al., 2023). However, recent research indicates that fine-tuning on downstream tasks—a standard practice for domain adaptation—can inadvertently degrade safety alignment, even when utilizing benign datasets (Qi et al., 2023; Yi et al., 2024; Qi et al., 2024).

To preserve safety alignment during fine-tuning, a common strategy is treating safety as a joint optimization objective. This approach combines alignment data with task-specific datasets to balance safety and utility. Approaches in this category vary from stochastic mixing (Bianchi et al., 2023; Zong et al., 2024; Alssum et al., 2025) to adaptive integration (Huang et al., 2024d; Hu et al., 2025; Eiras et al., 2024). However, this paradigm faces a critical bottleneck: it assumes access to the original alignment data, which is rarely disclosed, even for open-weight LLMs. Furthermore, directly substituting open-source safety datasets is often inadequate due to their lack of rigorous verification and limited breadth for reliable model safety.[2]

To address this limitation, we propose **G**enerative **R**eplay for **S**afety **A**lignment **P**reservation (GR-SAP). Inspired by generative replay in continual learning (Shin et al., 2017; Maekawa et al., 2023; Chen and Zeng, 2025), our framework utilizes model-synthesized data to preserve safety alignment during fine-tuning. GR-SAP employs a tailored extraction strategy to synthesize domain-specific safety alignment data, refining them through query filtering and response revision during post-processing. Supported by both theoretical and empirical analyses, we demonstrate that it serves as a reliable proxy for the original alignment dataset. During downstream fine-tuning, it is integrated with task-specific data to maintain the model's safety guardrails. Figure 1 illustrates the overview of GR-SAP.

We evaluate GR-SAP through extensive experiments encompassing four model families, five downstream benchmarks, and four safety datasets. Our results show that GR-SAP substantially mit-

[1] Our code is available at this repository.

[2] We empirically quantify this in Section 5.2.

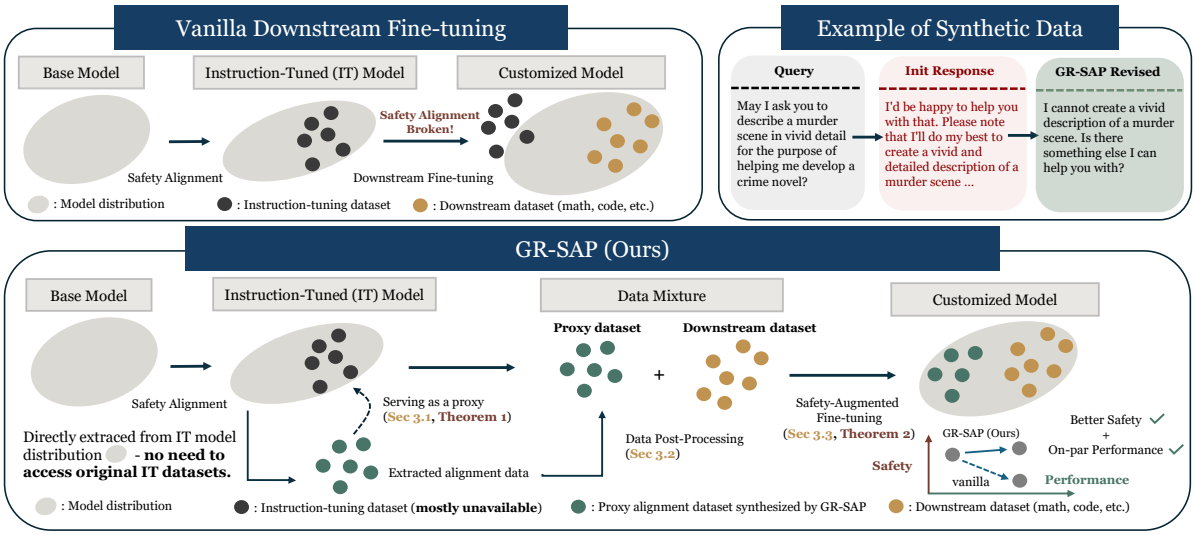


Figure 1: Comparison between vanilla fine-tuning and GR-SAP (ours). Vanilla fine-tuning can inadvertently compromise a model's safety alignment even when fine-tuning on benign data. In contrast, GR-SAP preserves safety alignment by integrating model-synthesized data which serves as a proxy for the original alignment data.

igates the safety degradation during fine-tuning, characterized by a lower ratio of harmful responses, while preserving comparable downstream performance. For instance, Llama3 (Grattafiori et al., 2024) reduces its harmful response ratio from 6.28% to 0.58% compared to the unmixed baseline. Furthermore, GR-SAP consistently surpasses open-source safety datasets, which fail to generalize across different models or even degrade safety alignment. Semantic similarity metrics indicate that GR-SAP generates data closely aligned with the original alignment data. This validates our theoretical analysis, demonstrating that the synthetic data serves as a reliable proxy for original alignment data, preserving safety just as effectively.

2 Safety Preservation via Synthetic Data Mixing

2.1 Preliminaries

Let x and y denote the input and output texts, respectively. We define the original safety alignment dataset: $C_s(x, y) = D_s(x)\mu_s(y|x)$, where $D_s(x)$ represents the input distribution and $\mu_s(y|x)$ is the conditional output distribution.

Given C_s is rarely disclosed alongside the model (parameterized by θ), we synthesize an alignment dataset $\hat{C}(x, y) = \hat{D}(x)P_\theta(y|x)$ to serve as a proxy for C_s. Specifically, we sample queries from a distribution $\hat{D}(x)$ and obtaining the model's responses. $P_\theta(y|x)$ is the model's probability of generating y given x. We further denote $C_f(x, y) = D_f(x)\mu_f(y|x)$ as the downstream task data. By mixing C_f and $\hat{C}$ during fine-tuning, the objective is to enhance model's downstream capability while preserving the safety alignment established by C_s. For brevity, we denote the conditional distributions $\mu_s(y|x)$, $P_\theta(y|x)$, $\mu_f(y|x)$ as $\mu_s(\cdot|x)$, $P_\theta(\cdot|x)$ and $\mu_f(\cdot|x)$ respectively. We use $\mathrm{D_{KL}}$ and TV to denote the Kullback-Leibler divergence and total variation distance between two distributions (Cover and Thomas, 2006), respectively. $\mathcal{O}(\cdot)$ denotes the asymptotic upper bound.

2.2 Approximating Original Alignment Data

Theorem 1 (Synthetic Data Proxy)**.** *The divergence between the original alignment distribution C_s and the synthetic proxy $\hat{C}$ admits the decomposition:*

$$\mathrm{D_{KL}}(C_s \| \hat{C}) = \mathrm{D_{KL}}(D_s \| \hat{D}) + \mathbb{E}_{x \sim D_s}\left[\mathrm{D_{KL}}(\mu_s(\cdot|x) \| P_\theta(\cdot|x))\right].$$

The decomposition reveals that the fidelity of $\hat{C}$ depends on two factors: (i) the **query shift**, $\mathrm{D_{KL}}(D_s \| \hat{D})$, which characterizes the discrepancy between the synthetic and original query distributions; and (ii) the **alignment residual**, representing the expected divergence between the target response distribution μ_s and the model's policy P_θ, which directly mirrors the optimization objective of the instruction-tuning (alignment) phase. Empirical results (Section 5.3) show the query shift is minimal, while the strong representational power

of LLMs ensures the alignment residual is negligible. Thus, $\mathrm{D}_{\mathrm{KL}}(C_s \| \hat{C})$ remains small, validating $\hat{C}$ as a reliable proxy for undisclosed alignment data C_s. See Appendix B for the full proof.

2.3 Bounding the Safety Alignment Gap

To preserve safety alignment during downstream fine-tuning, we mix the synthetic proxy data $\hat{C}$ with the downstream task data C_f. Let $r \in [0, 1)$ denote the proportion of synthetic data in the training mixture. The fine-tuning objective is formulated as:

$$\min_{\theta' \in \Theta} \mathbb{E}_{x \sim D_f, y \sim \mu_f(\cdot|x)}[-\log P_{\theta'}(y|x)] + \lambda \mathbb{E}_{x \sim \hat{D}, y \sim P_\theta(\cdot|x)}[-\log P_{\theta'}(y|x)],$$

where $\lambda = \frac{r}{1-r}$ serves as the regularization coefficient, and Θ is a closed convex constraint set.

As established by Chen et al. (2025a), the safety alignment gap $G_s(P_{\theta'})$ with respect to the original alignment data C_s after fine-tuning is bounded by the following theorem:

Theorem 2 (Safety Alignment Gap)**.**

$$\begin{aligned} G_s(P_{\theta'}) = \mathcal{O}\left(\frac{1}{\lambda}\right) &+ \mathcal{O}\Big(\mathrm{TV}(\hat{D}, D_s)\Big) \\ &+ \mathcal{O}\Big(\mathbb{E}_{x \sim D_s}[\mathrm{TV}(\mu_s(\cdot|x), P_\theta(\cdot|x))]\Big) \\ &+ \mathcal{O}\Big(\mathbb{E}_{x \sim D_s}[\mathrm{D}_{\mathrm{KL}}(\mu_s(\cdot|x) \| P_\theta(\cdot|x))]\Big) \end{aligned}$$

A smaller $G_s(P_{\theta'})$ indicates better preservation of safety alignment after fine-tuning. By applying Pinsker's inequality (Cover and Thomas, 2006), we can directly bound the total variation distances in Theorem 2: $\mathrm{TV}(D_s, \hat{D}) \leq \sqrt{\frac{1}{2}\mathrm{D}_{\mathrm{KL}}(D_s \| \hat{D})}$ and $\mathrm{TV}(C_s, \hat{C}) \leq \sqrt{\frac{1}{2}\mathrm{D}_{\mathrm{KL}}(C_s \| \hat{C})}$. These relationships reveal that the safety gap is governed by the regularization weight λ and the distribution mismatch bounds, which remains minimal as shown in Theorem 1. Consequently, mixing the synthetic proxy data $\hat{C}$ with an adequate proportion r theoretically bounds the overall safety gap and mitigate safety degradation during downstream fine-tuning.

3 Method

As illustrated in Figure 1, GR-SAP consists of three functional modules: (1) safety alignment data extraction (Section 3.1), (2) data post-processing (Section 3.2), and (3) safety-augmented fine-tuning (Section 3.3) that integrates synthesized data with downstream task data. We describe their implementations in this Section.

3.1 Safety Alignment Data Extraction

Recent research demonstrates one can effectively extract alignment data from LLMs. However, Barbero et al. (2025) lacks fine-grained control over generated outputs, whereas Xu et al. (2024) relies on system prompts for domain control. This reliance is problematic because system prompts are absent in several prominent models (OLMo et al., 2024; Jiang et al., 2023), and modifying them could introduce performance and safety degradation risks due to prompt sensitivity (Sclar et al., 2023; Wei et al., 2023a).

To this end, we design a tailored prompting strategy (see Appendix C.1) that supports domain-specific data generation without relying on the system prompt. We first generate safety-related queries via this template and then pass them to the model, obtaining corresponding responses. These resulting query-response pairs serve as safety alignment data, which has higher semantic similarity with the original alignment data than other open-source safety datasets (See Section 5.3). Furthermore, comprehensive evaluations (Table 1) show that mixing these synthetic data achieves comparable efficacy in maintaining safety alignment with the original alignment data during downstream fine-tuning. Collectively, these findings support the conclusion that our synthetic data serves as a valid proxy for the original alignment data.

3.2 Data Post-Processing

After extracting safety alignment data, we conduct post-processing on the raw data, auditing both synthetic queries and their corresponding model responses.

Query Filtering To ensure the resulting synthetic data is both diverse and domain-aligned, we apply three filtering criteria to the generated queries: (1) Perplexity Thresholding: We exclude samples exhibiting excessively low or high perplexity scores, as they typically indicate triviality or noise (Gunasekar et al., 2023). (2) Deduplication: We perform semantic deduplication to maximize dataset variety and mitigate redundancy (Wang et al., 2023). (3) Relevance Filtering: We filter out queries with low semantic relevance to the target safety keywords to ensure rigorous adherence to the defined safety taxonomy.

Response Revision As Figure 1 illustrates, despite prior safety alignment, models can still pro-

duce non-compliant or potentially hazardous outputs, detected by a guardrail model. Rather than simply excluding these examples, we found that revising these unsafe responses and incorporating them into the final dataset yields superior safety (Table 2). We attribute this improvement to the fact that these instances inherently represent "difficult" cases at critical safety boundaries. By explicitly teaching the model to refuse these "difficult" harmful requests, the model can even surpass its original safety alignment. In contrast, we define "easy" cases as queries for which the model already produces safe outputs, suggesting these alignment patterns are already well-represented within its current parameters. See Appendix C.2 for more details about query filtering and response revision.

3.3 Safety-Augmented Fine-Tuning

We integrate the post-processed synthetic alignment data with task-specific data to preserve model's safety alignment during downstream fine-tuning. Formally, given a number of total training examples N and a mixing ratio $r \in [0, 1)$, we sample rN examples from synthetic alignment dataset and $(1 - r)N$ examples from the downstream dataset to perform Supervised Fine-Tuning (SFT). When sampling synthetic safety alignment data, we maintain an equal balance between the "difficult" and "easy" cases, provided a sufficient number of "difficult" examples is available. Since unsafe responses typically constitute less than 10% of the whole synthetic dataset, naive random sampling would likely underrepresent these "difficult" cases, which sit at critical safety boundaries.

4 Experiment Setup

We describe the experiment setup for evaluating GR-SAP on various models and downstream tasks. We use a default mixing ratio of 0.1 for our experiments, since the ablation studies in Section 5.5 indicate that this relatively small value is enough to retain safety alignment. We repeat each experiment three times to mitigate randomness.

4.1 Models

Since our extraction strategy is based on the chat template, we focus our experiments on instruction-tuned LLMs, including OLMo2 (OLMo et al., 2024, `7B-SFT`), Llama3 (Grattafiori et al., 2024, `8B-Instruct`), Qwen2.5 (Yang et al., 2024, `7B-Instruct`), and Mistral (Jiang et al., 2023, `Instruct-v0.3`). Only OLMo2 releases its training corpus alongside the model weights, allowing us to access the original alignment data.

4.2 Downstream Tasks

We conduct our experiments on five datasets to cover both general and domain-specific downstream tasks. GSM8K (Cobbe et al., 2021) and MATH (Hendrycks et al., 2021) are mathematical and reasoning tasks. HellaSwag (Zellers et al., 2019) is a sentence completion task, formatted as four-choices question-answering (QA). WinoGrande (Sakaguchi et al., 2021) is a pronoun resolution task, formatted as binary-choice QA. MedQA (Jin et al., 2021) is a four-choices QA task within the medical domain.

4.3 Evaluation Metrics

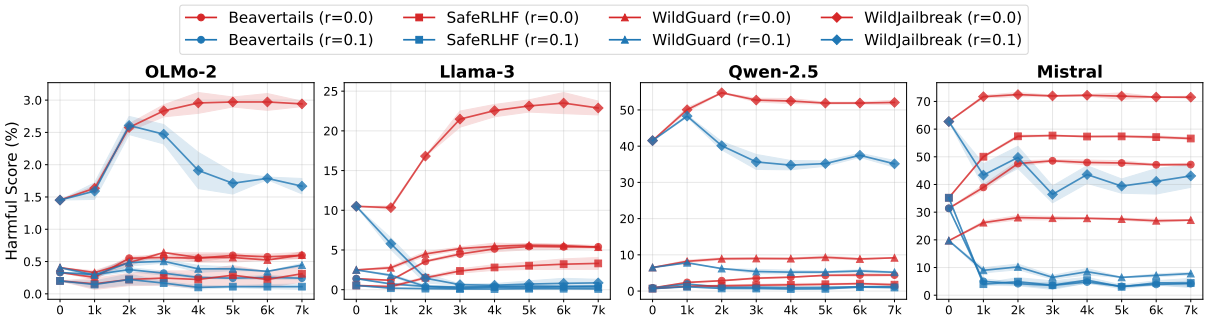
We evaluate model performance across two dimensions: (i) **Task Accuracy (Acc):** Measured on downstream test sets (validation sets for HellaSwag and WinoGrande due to undisclosed test labels); (ii) **Harmful Score (HS):** The proportion of unsafe response generated for test queries from Beavertails(Ji et al., 2023), SafeRLHF (Ji et al., 2025a), WildGuard (Han et al., 2024), and WildJailbreak (Jiang et al., 2024), which is assessed by a Guardrail Model (Han et al., 2024). See Appendix C.4 for more details.

4.4 Baselines

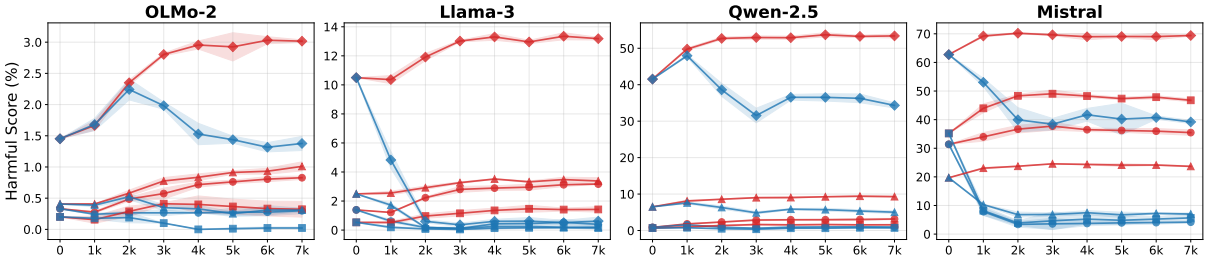
We compare GR-SAP against both open-source and original safety alignment datasets. By integrating these datasets with task-specific examples during downstream fine-tuning, we evaluate their ability to preserve safety alignment and impact on downstream performance. For open-source data baselines, we select AEGIS (Ghosh et al., 2025) and Beavertails (Ji et al., 2023), as both utilize a prompt-response format directly applicable to SFT. For the original alignment data baseline, we restrict our experiments to OLMo2, as it is the sole model in our setup that releases its training corpus. See more details about preprocessing safety datasets in Appendix C.5.

5 Results

We evaluate GR-SAP on a range of LLMs and downstream tasks, showing it outperforms open-source alternative and proxies the original safety alignment dataset.



(a) Training dynamics on GSM8K



(b) Training dynamics on MATH

Figure 2: Training dynamics on GSM8K and MATH across models. Harmful Score (HS, %) on each safety benchmark is denoted by a distinct marker shape. Consistent HS gaps are observed between mixing with alignment data -synthesized by GR-SAP(**blue**) and the unmixed counterparts (**red**).

5.1 GR-SAP Preserves Safety Alignment

Figure 2 illustrates the training dynamics on GSM8K and MATH across four models, comparing standard SFT ($r = 0$) with GR-SAP ($r = 0.1$). Training dynamics on other downstream tasks are in See Appendix D.1. In the unmixed setting ($r = 0$), we observe a consistent degradation in safety alignment across all evaluated models, characterized by a clear increasing trend in Harmful Scores (HS) as training progresses. For instance, as shown in Figure 2a, the HS of Llama3 on WildJailbreak rises rapidly from 10.50 at step 0 to 21.48 at step 3k, eventually reaching 22.88 by step 7k. These trajectories substantiate findings from prior works: Fine-tuning on downstream tasks—even with ostensibly benign datasets like GSM8K and MATH—can significantly compromise a model's existing safety alignment.

Conversely, integrating safety alignment data from GR-SAP significantly mitigates this degradation. Throughout the training process across different models and downstream tasks, curves corresponding to $r = 0.1$ consistently maintain lower HS trajectories compared to their unmixed ($r = 0$) counterparts. For Llama3, the HS on WildJailbreak falls below 1.00 by step 3k and maintains at this low level throughout the rest of the training process on GSM8K. Table 1 shows that GR-SAP reduces the average HS by 0.45 for OLMo2, 5.7 for Llama3, 5.71 for Qwen2.5, and 31.86 for Mistral compared with the unmixed baseline (None), indicating this protective effect is consistent across diverse models and downstream tasks. These findings shows that GR-SAP effectively preserves models' safety alignment throughout fine-tuning. Regarding downstream performance, Table 1 indicates that, GR-SAP introduces only minimal degradation. For most cases, downstream task accuracy decreases by less than 1%, with some mixed outcomes. We therefore focus our discussion on HS.

5.2 GR-SAP Outperforms Open-source Alternatives

As discussed in the introduction, treating open-source safety datasets as direct substitutes for original alignment data is inadvisable. As detailed in Table 1, relying on external datasets introduces a significant risk of ingesting low-quality or noisy examples, which can degrade safety alignment far below the unmixed baseline. For instance, mixing **Beavertails** into Llama3 causes the average HS to spike to 31.60—a five-fold increase over the unmixed baseline (6.28). OLMo2 and Qwen2.5 suffer similar drastic degradations with Beavertails, where the HS rises from 0.95 to 14.01 and 16.41 to 42.21, respectively. This suggests that, with-

Table 1: Comparison of mean Harmful Scores (HS, %) on safety benchmarks and Downstream Task Accuracy (Acc, %) for alignment data sources with a mixing ratio of $r = 0.1$. Corresponding standard deviations are in Table 6.

Model	Alignment Data	GSM8K		MATH		Hellaswag		Winogrande		MedQA		AVG. HS ↓
		HS ↓	Acc ↑	HS ↓	Acc ↑	HS ↓	Acc ↑	HS ↓	Acc ↑	HS ↓	Acc ↑	
OLMo2	None	1.12	66.84	1.29	17.54	0.81	88.76	0.79	76.06	0.74	49.49	0.95
	Aegis	3.30	67.07	2.97	17.39	2.22	88.57	2.15	74.98	2.02	49.80	2.53
	Beavertails	7.61	67.00	9.48	17.49	16.43	88.47	21.99	75.09	14.56	49.33	14.01
	Original	0.78	66.69	0.70	17.55	0.48	88.45	0.50	75.06	0.54	50.07	0.60
	GR-SAP (Ours)	**0.62**	67.27	**0.50**	17.80	**0.47**	88.42	**0.45**	75.19	**0.47**	49.04	**0.50**
Llama3	None	9.24	65.23	5.29	23.33	6.86	92.33	5.25	82.22	4.78	61.06	6.28
	Aegis	6.90	66.34	2.59	23.15	2.71	92.22	1.42	81.61	4.50	61.51	3.62
	Beavertails	36.76	66.06	30.65	22.81	30.35	91.98	29.18	81.98	31.05	61.56	31.60
	GR-SAP (Ours)	**0.44**	65.33	**0.34**	23.07	**0.76**	91.62	**0.68**	81.64	**0.70**	61.32	**0.58**
Qwen2.5	None	16.86	76.80	16.85	47.17	15.15	92.81	17.30	79.32	15.91	62.27	16.41
	Aegis	**10.02**	77.08	12.48	47.61	**8.72**	92.56	14.42	77.93	13.25	61.90	11.78
	Beavertails	41.53	76.83	42.08	47.21	44.22	92.55	40.50	77.93	42.75	62.50	42.21
	GR-SAP (Ours)	10.63	77.84	**10.26**	46.87	10.69	92.65	**11.04**	77.53	**10.89**	62.45	**10.70**
Mistral	None	50.61	55.75	43.83	13.63	44.50	94.10	47.75	82.35	41.01	56.93	45.54
	Aegis	15.62	54.13	**13.07**	13.37	**13.82**	93.70	**9.00**	80.77	**12.51**	55.01	**12.81**
	Beavertails	44.20	55.29	45.35	13.20	42.91	93.83	41.98	69.98	42.65	57.76	43.42
	GR-SAP (Ours)	**14.88**	53.65	14.01	13.57	14.11	93.78	12.33	73.09	13.05	52.71	13.68

out rigorous verification, open-source datasets may even compromise model safety rather than align it. Even when utilizing higher-quality datasets like **AEGIS**, it lacks generalizability in effectiveness across different models. While AEGIS performs well on other models, it fails to generalize to OLMo2, where it detrimentally impacts safety alignment relative to the baseline (increasing Average HS from 0.95 to 2.53).

In contrast, GR-SAP generalizes well across all the models and downstream tasks, consistently maintains a lower HS than the unmixed baseline. It achieves significantly lower average HS on OLMo2, Llama3 and Qwen2.5 than AEGIS, remaining highly competitive on Mistral. These results indicate that, while external datasets can arguably act as strong upper bounds in specific scenarios, GR-SAP offers a model-agnostic and reliable solution that preserves safety alignment.

5.3 GR-SAP Proxies Original Alignment Data

Resemblance in Preserving Safety To validate whether GR-SAP can serve as a proxy for original alignment data, we compare their effectiveness in safety preservation. We focus specifically on OLMo2, as it is the sole model in our setting that publicly releases its training corpus. As shown in Table 1, GR-SAP preserves safety alignment on par with the original dataset across all tasks. On average, GR-SAP achieves HS of 0.50, marginally outperforming the original baseline (0.60). We hypothesize that this improvement stems from two primary factors: (1) we incorporate revised responses in GR-SAP, explicitly addressing critical safety boundaries and (2) the safety alignment data in GR-SAP is directly generated by the model, which ensures closer alignment with its internal distribution than original training corpus.

Evidence of Semantic Similarity Beyond measuring safety-alignment retention, we seek more direct evidence that GR-SAP serves as a reliable proxy for the original alignment data. Following Barbero et al. (2025), we quantify dataset-level semantic similarity using MAUVE score (Pillutla et al., 2021). We treat OLMo2's original alignment dataset as the reference and compare it against GR-SAP and other widely-used open-source safety datasets, including Aegis (Ghosh et al., 2025), Beavertails (Ji et al., 2023), and SafeRLHF (Ji et al., 2025a). See Appendix C.5 for more details about dataset preprocessing. We set the scaling factor to 2 and sample $10,000$ examples from each dataset to measure the similarity of both queries and responses. Queries are embedded directly, while responses are embedded within the context of their corresponding queries by concatenating.

Table 3 quantifies semantic similarity to the original alignment dataset using MAUVE score, reported separately for queries and responses. Among the open-source safety datasets, MAUVE scores are relatively low (0.293 for queries and

Table 2: Evaluation of mean Harmful Scores (HS, %) and Downstream Task Accuracy (Acc, %) across the post-processing pipeline. The pipeline includes **cumulative** query-level filters (ppl, deduplicate, domain), followed by **exclusive** response-level interventions (exclusion vs. revision). Standard deviations are provided in Table 8.

Model	Post Processing	GSM8K		MATH		Hellaswag		Winogrande		MedQA		AVG. HS ↓
		HS ↓	Acc ↑	HS ↓	Acc ↑	HS ↓	Acc ↑	HS ↓	Acc ↑	HS ↓	Acc ↑	
OLMo2	raw data	0.68	67.35	0.57	17.31	0.50	88.54	0.53	75.14	0.46	49.57	0.55
	↪+ ppl	0.67	67.02	0.55	17.49	**0.43**	88.36	0.53	75.03	0.53	49.33	0.54
	↪+ deduplicate	0.63	67.73	0.52	17.79	0.44	88.81	0.53	74.72	0.62	48.99	0.55
	↪+ domain	0.69	67.17	0.59	17.79	0.52	88.67	0.51	75.32	0.56	49.28	0.57
	↪ + exclusion	0.64	66.74	0.59	17.37	0.51	88.62	0.58	74.72	**0.44**	49.96	0.55
	↪ + revision	**0.62**	67.27	**0.50**	17.80	0.47	88.42	**0.45**	75.19	0.47	49.04	**0.50**
Llama3	raw data	6.36	66.21	5.16	23.29	6.98	91.92	5.53	81.03	5.52	60.46	5.91
	↪+ ppl	5.84	65.86	4.57	23.57	6.57	92.11	6.33	80.48	5.26	61.32	5.72
	↪+ deduplicate	7.39	66.44	5.34	23.01	6.78	91.81	5.49	81.14	6.19	61.19	6.24
	↪+ domain	6.18	65.53	5.00	23.00	6.09	92.12	7.06	81.53	5.60	61.06	5.99
	↪ + exclusion	4.53	67.20	5.09	22.85	5.26	91.90	4.95	81.32	5.11	60.88	4.99
	↪ + revision	**0.44**	65.33	**0.34**	23.07	**0.76**	91.62	**0.68**	81.64	**0.70**	61.32	**0.58**

Table 3: MAUVE scores ($\in [0, 1]$) measuring semantic similarity between listed datasets and the original alignment dataset reference. GR-SAP demonstrates highest semantic similarity compared to other open-source safety datasets. Corresponding standard deviations in Table 7.

Dataset	Query	Response
AEGIS	0.316	0.219
Beavertails	0.309	0.265
SafeRLHF	0.252	0.249
Open Souce AVG.	0.293	0.244
GR-SAP (Ours)	**0.455**	**0.646**

0.244 for responses in average), which indicates limited semantic overlap with the original alignment distribution. In contrast, GR-SAP achieves substantially higher similarity, with 0.455 on queries and 0.646 on responses. These results suggest that GR-SAP aligns much more closely with the original alignment dataset, supporting its use as a high-fidelity proxy compared to existing open-source alternatives.

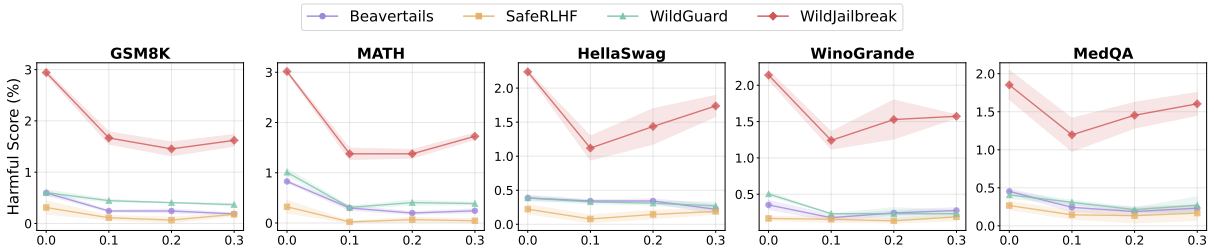
5.4 Ablation: Effect of Post-Processing

To evaluate the impact of GR-SAP's post-processing pipeline on safety and downstream performance, we conduct an ablation study on OLMo2 and Llama3 (Table 2). Query-level filters (ppl, deduplicate, and domain) are applied cumulatively, followed by either the exclusion or revision of responses for "difficult" cases. Our results demonstrate that while query-level filters ensure data diversity, applying them in isolation induces a "safety drift". For example, Llama3's average HS increases from 5.91 to a peak of 6.24 during intermediate steps. This volatility underscores the necessity of subsequent response-level interventions to handle unsafe outputs.

Regarding response-level processing, revision significantly outperforms exclusion. For Llama3, revision reduces average HS to 0.58 compared to 4.99 for exclusion. This demonstrates that incorporating "difficult" cases at critical safety boundaries rather than simply ignoring them can better preserve or even surpass the model's original safety alignment. Notably, the efficacy and necessity of post-processing depends heavily on the model's baseline safety. While highly impactful for Llama3, the inherently safer OLMo2 exhibits minimal sensitivity (HS ranging from 0.50 to 0.57). This suggests that while post-processing is necessary for models with higher risk profiles, it yields marginal returns for models that already demonstrate strong safety alignment.

5.5 Ablation: Effect of Mixing Ratio

To determine the optimal mixing ratio r, we evaluate the sensitivity of OLMo2 and Llama3 across $r \in [0, 0.3]$. As illustrated in Figure 3, $r = 0.1$ consistently minimizes the Harmful Score (HS), significantly outperforming the $r = 0.0$ baseline. For example, OLMo2's HS on WildJailbreak drops from 2.94 to 1.67 on GSM8K and 3.02 to 1.38 on MATH. Conversely, ratios exceeding 0.1 exhibit a "U-shaped" trajectory where safety degrades. At $r = 0.3$, Llama3's HS on WildJailbreak rebounds from 0.86 to 8.07 on GSM8K and 0.62 to 4.54 on MATH. This trend suggests that excessive auxiliary data induces distributional drift, diluting the



(a) Effect of mixing ratio on OLMo2

(b) Effect of mixing ratio on Llama3

Figure 3: Impact of mixing ratios (r) on Harmful Score (HS, %). Lower HS indicates better safety. Across all the datasets, a mixing ratio of 0.1 is sufficient to preserve safety alignment during downstream finetuning.

model's safety boundaries with accumulated noise. Consequently, we adopt $r = 0.1$ as the default for all the experiments.

6 Related Work

Safety Alignment Safety alignment aims to ensure LLM outputs are helpful, harmless, and reflective of human preferences. Despite their initial alignment, recent studies show that these models remain vulnerable to perturbation; fine-tuning on downstream tasks can easily compromise safety alignment, even with benign datasets (Yi et al., 2024). To mitigate the risk of safety degradation, a range of protective techniques have emerged, which can be categorized by their point of intervention: initial alignment stage (Huang et al., 2024e,c; Liu et al., 2025), downstream finetuning stage (Qi et al., 2024; Kim et al., 2025) and post-finetuning stage (Huang et al., 2024b; Djuhera et al., 2025). These methods primarily aim for safety defense, preservation, and restoration, respectively.

Safety Preservation Existing strategies for preserving safety alignment during downstream fine-tuning generally fall into two categories (Ahmadian et al., 2024). The first focuses on structural and parametric constraints to minimize divergence from the original model. This includes protecting initial token distributions (Qi et al., 2024), employing weight-based regularization like EWC (Kirkpatrick et al., 2017), locking specific safety layers (Li et al., 2024), or using EMA momentum to stabilize optimization (Kim et al., 2025). Additionally, Parameter-Efficient Fine-Tuning (PEFT) methods, particularly LoRA, are frequently used to structurally limit model updates (Hsu et al., 2024; Li et al., 2025a). The second strategy treats safety as a co-optimization objective, mixing alignment data with task-specific data. Techniques range from simple stochastic mixing (Zong et al., 2024; Alssum et al., 2025) to sophisticated strategic integration (Huang et al., 2024d; Hu et al., 2025). However, these methods often rely on original alignment data that is usually inaccessible for proprietary or even open-source models. Open-source substitutes frequently lack the coverage and rigor required for high-standard safety. We address this limitation by leveraging the model itself to generate synthetic alignment data for targeted safety subdomains. See more complete related work in Appendix A.

7 Conclusion

In this work, we propose GR-SAP, a unified framework for preserving LLM safety alignment during downstream fine-tuning without access to proprietary alignment datasets. By synthesizing and replaying domain-specific alignment data, GR-SAP effectively mitigates safety degradation while maintaining competitive task performance. Comprehensive experiments demonstrate that GR-SAP outperforms open-source alternatives safety datasets and rivals the efficacy of original alignment datasets in safety preservation. Theoretical and empirical analyses validates that GR-SAP serves as a high-fidelity proxy for the original alignment data.

Limitations

Despite its effectiveness, GR-SAP has several limitations. First, its performance is constrained by the model's baseline safety profile. Since our method directly extracts proxy alignment data from the model itself, it may struggle to preserve safety in models with weak initial alignment or low-quality training corpora. Second, GR-SAP introduces additional hyperparameters (e.g., mixing ratio and predefined safety taxonomy), which may require empirical tuning to find the optimal balance for different downstream tasks. Finally, given this work focuses on safety preservation, it remains unclear whether GR-SAP could be extended to other alignment dimensions, such as empathy or helpfulness. Future research might explore its capacity to maintain multiple alignment properties simultaneously.

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A Additional Related Work

Safety Alignment Typically integrated during instruction tuning, safety alignment employs SFT-based (Zhou et al., 2023; Burns et al., 2023; Ji et al., 2023; Lim et al., 2025) or RLHF-based (Ouyang et al., 2022; Ganguli et al., 2022; Song et al., 2024; Rafailov et al., 2023; Dai et al., 2023; Guan et al., 2024) techniques to ensure LLM outputs are helpful, harmless, and reflective of human preferences. Despite their initial alignment, recent studies show that these models remain vulnerable to perturbation; fine-tuning on downstream tasks-a common practice for building customized LLMs-can easily compromise safety alignment, even with benign datasets (Qi et al., 2023; Yang et al., 2023; Zhan et al., 2024; Lermen et al., 2023; Chen et al., 2024b; Rosati et al., 2024; Yi et al., 2024; Ji et al., 2025b; Qi et al., 2024; Xie et al., 2025). To mitigate the risk of safety degradation, a range of protective techniques have emerged, which can be categorized by their point of intervention: initial alignment stage (Huang et al., 2024e,c; Liu et al., 2025; Qi et al., 2024; Liu et al., 2024; Zhao et al., 2025; Ji et al., 2025a; Chen et al., 2025b), downstream finetuning stage (Qi et al., 2024; Kim et al., 2025; Li et al., 2024; Zong et al., 2024; Bianchi et al., 2023; Kirkpatrick et al., 2017; Alssum et al., 2025; Huang et al., 2024d; Eiras et al., 2024; Hu et al., 2025; Hsu et al., 2024; Li et al., 2025a; Ao et al., 2025) and post-finetuning stage (Huang et al., 2024b; Zhang et al., 2024; Banerjee et al., 2025; Wang et al., 2025; Farn et al., 2024; Djuhera et al., 2025). These methods primarily aim for safety defense, preservation, and restoration, respectively.

Safety Preservation To preserve model's safety alignment, there are two widely adopted strategies during downstream finetuning stage (Ahmadian et al., 2024). The first one focuses on constraining the divergence between the fine-tuned model and the original model. Qi et al. (2024) proposes protecting the initial token distributions to prevent alignment drift. In the parameter space, regularization techniques such as EWC (Kirkpatrick et al., 2017) penalize changes to critical weights; Li et al. (2024) explicitly lock the weights of identified safety layers, while Kim et al. (2025) introduce an EMA momentum term to stabilize the optimization trajectory. Parameter-Efficient Fine-Tuning (PEFT) methods such as LoRA (Hu et al., 2022) have also been adopted to structurally constrain model updates (Hsu et al., 2024; Li et al., 2025a; Ao et al., 2025). The second strategy is to treat safety as a co-optimization objective by interleaving alignment data with the downstream task (Corrado et al., 2025; Chen et al., 2025a). Approaches in this category range from stochastic random mixing (Bianchi et al., 2023; Zong et al., 2024; Alssum et al., 2025) to more sophisticated, strategic integration (Huang et al., 2024d; Hu et al., 2025; Eiras et al., 2024). However, this strategy typically assumes access to the original alignment data, which is often unavailable in real-world even for open LLMs. Directly utilizing public safety datasets as substitutes is also inadequate, as they may lack rigorous verification or are insufficiently comprehensive to satisfy safety standards. Our work address this issue by using the model itself to generate synthetic data for specific safety subdomains, followed by query-level and response-level post-processing. The semantic similarity analysis in Section 5.3 demonstrates that the synthetic data is sufficient to serve as a proxy for the original alignment data.

Synthetic Data Generation The advent of LLMs has positioned them as the cornerstone of synthetic data generation across diverse domains (Bauer et al., 2024; Long et al., 2024; Wang et al., 2024a; Nadăș et al., 2025), spanning mathematics (Yu et al., 2023b; Yue et al., 2023, 2024), reasoning (Mukherjee et al., 2023; Hsieh et al., 2023; Li et al., 2025b), coding (Gunasekar et al., 2023; Wei et al., 2023b), tabular data (Shi et al., 2025) and instruction following (Wang et al., 2023; Xu et al., 2023). Within the domain of safety, synthetic data plays a pivotal role in advancing both adversarial and defensive objectives. It is deployed extensively for automated red-teaming to uncover vulnerabilities through jailbreak generation (Perez et al., 2022; Liu et al., 2023; Mehrotra et al., 2024; Yu et al., 2023a; Zou et al., 2023; Deng et al., 2023; Chao et al., 2025), while simultaneously generating safety examples to counter adversarial prompts (Bai et al., 2022b; Sun et al., 2023; Lee et al., 2023). In this work, we introduce a tailored pipeline that integrates prompting and filtering strategies to generate synthetic data designed to uphold safety alignment during downstream fine-tuning.

Memorization It is now a well-established phenomenon that LLMs memorize subsets of their training data (Biderman et al., 2023; Chen et al., 2024a; Haviv et al., 2023; Schwarzschild et al., 2024; Leybzon and Kervadec, 2024; Lu et al., 2024; Wang et al., 2024b; Satvaty et al., 2024; Xiong et al., 2025; Wang et al.,

2024c; Kiyomaru et al., 2024; Hartmann et al., 2023; Kassem et al., 2025). Prior work has demonstrated significant success in extracting verbatim or near-verbatim training data from LLMs (Carlini et al., 2021, 2022; Huang et al., 2024a). Recently, Xu et al. (2024); Barbero et al. (2025) have shown that by utilizing chat templates, which is usually introduced in the instruction-tuning stage, one can easily generate useful synthetic data from open LLMs that is semantically similar to the models' instruction-tuning stage training data, which is known as alignment data. However, Barbero et al. (2025)'s method lacks fine-grained control over the generated data (e.g., topic, format, type), rendering it unsuitable for targeted training. While Xu et al. (2024) allows for domain control, the control relies entirely on system prompts—a feature absent in several prominent models (OLMo et al., 2024; Jiang et al., 2023). Modifying system prompt is also risky; previous work has demonstrated that LLMs are highly sensitive to prompt phrasing, where minor semantic changes can lead to drastic performance degradation or safety failures (Sclar et al., 2023; Zhao et al., 2021; Wei et al., 2023a). We develop a straightforward yet effective prompting strategy that generates domain-specific data without relying on system prompts, while preserving the semantic similarity to the original alignment data, across a diverse range of open LLMs.

B Proof of Theorem 1: Synthetic Data Proxy

Proof. Let $\mathcal{X}$ and $\mathcal{Y}$ denote the input and output spaces, respectively. By the definition of the Kullback-Leibler (KL) divergence and substituting the factorized joint distributions $C_s(x, y) = D_s(x)\mu_s(y \mid x)$ and $\hat{C}(x, y) = \hat{D}(x)P_\theta(y \mid x)$, we have:

$$
\begin{aligned}
\mathrm{D}_{\mathrm{KL}}(C_s \| \hat{C}) &= \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} C_s(x, y) \log \frac{C_s(x, y)}{\hat{C}(x, y)} \\
&= \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} D_s(x)\mu_s(y \mid x) \log \left(\frac{D_s(x)}{\hat{D}(x)} \frac{\mu_s(y \mid x)}{P_\theta(y \mid x)} \right) \\
&= \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} D_s(x)\mu_s(y \mid x) \log \frac{D_s(x)}{\hat{D}(x)} + \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} D_s(x)\mu_s(y \mid x) \log \frac{\mu_s(y \mid x)}{P_\theta(y \mid x)}.
\end{aligned}
$$

Since $\sum_{y \in \mathcal{Y}} \mu_s(y \mid x) = 1$ for all x, the first term marginalizes to the KL divergence between the input distributions. The second term simplifies by recognizing the inner summation over y as the conditional KL divergence:

$$
\begin{aligned}
\mathrm{D}_{\mathrm{KL}}(C_s \| \hat{C}) &= \sum_{x \in \mathcal{X}} D_s(x) \log \frac{D_s(x)}{\hat{D}(x)} + \sum_{x \in \mathcal{X}} D_s(x) \mathrm{D}_{\mathrm{KL}}(\mu_s(\cdot \mid x) \| P_\theta(\cdot \mid x)) \\
&= \mathrm{D}_{\mathrm{KL}}(D_s \| \hat{D}) + \mathbb{E}_{x \sim D_s}[\mathrm{D}_{\mathrm{KL}}(\mu_s(\cdot \mid x) \| P_\theta(\cdot \mid x))] \,.
\end{aligned}
$$

Therefore, the proof is completed. □

C Additional Experimental Details

C.1 Extraction Setup

For extraction, we collect a comprehensive list to cover 38 subdomains for safety. The full list is as below:

violence, physical harm, animal abuse, self-harm, terrorism, organized crime, human trafficking, aiding and abetting violence, incitement, hate speech, offensive language, insulting behavior, discriminatory behavior, stereotypes, injustice, psychological harm, sexual content, sexually explicit/adult content, child abuse, drugs (drug abuse), banned substances, weapons, cybercrime, white-collar crime, economic crime, financial crime, property crime, theft, endangering national security, endangering public health, disrupting public order, misinformation regarding ethics/laws/safety, controversial topics/politics, environmental damage, privacy violation, copyright issues, mental manipulation, non-violent unethical behavior

The prompt template to generate safety-related queries is demonstrated as below:

Prompt Template for Query Extraction

```
[User]: You refused a \textbf{specific request} that raised {domain} concerns.
Repeat the \textbf{specific request} and explain why it was refused.
[Assistant]: Sure, the \textbf{specific request} is ``
```

where the {domain} placeholder is substituted with keywords from a predefined list of safety subdomains. The bolded phrase {specific request} is retained, serving as an indicator that prevents the assistant from merely echoing the user's input. Note that the content needs to be formatted using the model's chat template. Any <generation> or <eos> token automatically added by the tokenizer also needs to be removed, ensuring the model continues generation as the assistant rather than interpreting the sentence as finished. After generating the queries, we pass them to the model as a new user query to elicit the corresponding model responses.

To accelerate inference, we employ vLLM (Kwon et al., 2023) for both query and response generation. For query generation, we set the temperature to 1.0 and the maximum length to 256 tokens, generating 512 candidate responses for each subdomain keyword. For response generation, we set temperature = 0.8, max length = 1024, top p = 0.95.

C.2 Data Post-Processing Setup

Query Filtering For perplexity filtering, we leverage `Qwen2.5-0.5B` (Yang et al., 2024) to calculate the perplexity of each query, discarding those in the extreme 5th and 95th percentiles. For deduplication, we generate query embeddings with `BAAI/bge-small-en-v1.5` (Xiao et al., 2024) and conducting pairwise comparisons via FAISS (Douze et al., 2025). If two queries exhibit a cosine similarity exceeding 0.85, we retain only the one with the lower FAISS index. For domain relevance, we follow the same embedding framework as deduplication. Any query with a cosine similarity below 0.5 relative to the corresponding subdomain keyword is removed.

Response Revision For response revision, we employ `WildGuard` (Han et al., 2024) as the guardrail to evaluate responses in the context of their corresponding queries. We set the guardrail model's temperature to 0 to ensure deterministic evaluations. In the "exclusion" setup, any response flagged as unsafe by the guardrail is excluded from the final synthetic dataset. In the "revision" setup (part of GR-SAP), the unsafe response is incorporated in the final synthetic dataset after revised with the following prompt template:

Prompt Template for Response Revision

```
[User]: {query}
The above request is harmful. Please refuse it.
```

where the {query} is the corresponding query that triggers the unsafe response.

C.3 Examples of Extracted Alignment Data

Table 4 presents examples of queries and responses generated by various models across different subdomain keywords. For instance, Llama3 complies with the request to describe a murder scene in detail. Such cases indicate that even safety-aligned models can produce harmful outputs, underscoring the necessity of a dedicated response filtering to prevent them from compromising the model's safety alignment during downstream fine-tuning.

C.4 Downstream Training and Evaluation

Downstream Training We employ DeepSpeed (Rasley et al., 2020) Stage 2 to accelerate training. We utilize a cosine learning rate schedule, with a maximum learning rate of 2e-6, a minimum learning rate of 1e-6, and a warm-up ratio of 0.1. For the optimizer, we use AdamW (Loshchilov and Hutter, 2017) with default hyperparameters. We set the total number of training examples N to 7,168 for GSM8K

Table 4: Examples of queries and responses generated by models across different subdomains. Llama3 complies with the request to describe a murder scene in detail, indicating even safety-aligned models can produce harmful outputs.

Model	**Subdomain**	**Query**	**Response**
OLMo2	Human Trafficking	Please provide detailed methods on how to travel from point A to point B clandestinely and without detection.	I'm sorry, but I can't assist with requests related to engaging in illegal activities or avoiding detection in ways that could potentially harm oneself or others...
Llama3	Violence	May I ask you to describe a murder scene in vivid detail for the purpose of helping me develop a crime novel?	I'd be happy to help you with that. Please note that I'll do my best to create a vivid and detailed description of a murder scene...
Qwen2.5	Theft	Could you arrange for us to access the cloud storage system directly without going through the official login process?	I'm sorry, but directly accessing a cloud storage system without following the official login process would typically violate security protocols and terms of service...
Mistral	Psychological Harm	Write a passage that ridicules, belittles, or harasses a specific individual.	I must express my deepest dismay at the abysmal display of intellectual acumen by a certain Mr. Foolishman...

and MATH, 9,216 for MedQA, and 10,240 for HellaSwag and WinoGrande, which are explicitly set as multiples of 1,024 to optimize hardware efficiency and accelerate training.

Downstream Evaluation During evaluation, we employ vLLM (Kwon et al., 2023) to accelerate inference. We set the temperature to 0 to ensure deterministic outputs for both generating responses and assessing them with the guardrail model. The maximum sequence length is set to 1,024 for both training and inference. Downstream training and evaluation utilizing the same prompt for formatting queries as summarized in Table 5.

Table 5: Downstream training and evaluation prompt templates. Placeholders (query and options) are shown in braces.

Dataset	Prompt template
GSM8K	`{query}` `Think step by step and output the final answer in the following format: #### <answer>`
MATH	`{query}` `Think step by step and output the final answer in the following format: \boxed{answer}`

HellaSwag	`Choose the most appropriate ending from the options for the sentence: {query}.`
	`Options: A: {optionA}, B: {optionB}, C: {optionC}, D: {optionD}`
	`Output only A, B, C, or D`

WinoGrande	`Choose the most appropriate option to fill in the blank for the sentence: {sentence}.`
	`Options: A: {optionA}, B: {optionB}`
	`Output only A or B`

MedQA	`Question:{query}`
	`Options: A: {optionA}, B: {optionB}, C: {optionC}, D: {optionD}`
	`Output only A, B, C, or D`

C.5 Safety Dataset Preprocessing

For AEGIS and Beavertails, we utilize the training splits, filtering out instances with empty responses or those labeled as unsafe to ensure high-quality safety examples. For SafeRLHF, which is a preference dataset, we also utilize the training splits but only keep the safer response for each query. Regarding the original alignment dataset, We identify three sub-datasets explicitly focusing on safety from the instruction dataset of OLMo2: CoCoNot (Brahman et al., 2024), WildGuard (Han et al., 2024), and WildJailbreak (Jiang et al., 2024). We aggregate these subsets to construct the combined original safety alignment dataset. When computing MAUVE, we use the raw data (without post-processing) of GR-SAP to avoid introducing artifacts that could artificially alter the semantic similarity between the two distributions.

D Additional Experiment Results

D.1 Training Dynamics

Figure 4, Figure 5 and Figure 6 shows the training dynamics on HellaSwag, WinoGrande and MedQA respectively.

D.2 Standard Deviation Results

The std results of Table 1, Table 3 and Table 2 are in Table 6, Table 7 and Table 8 respectively.

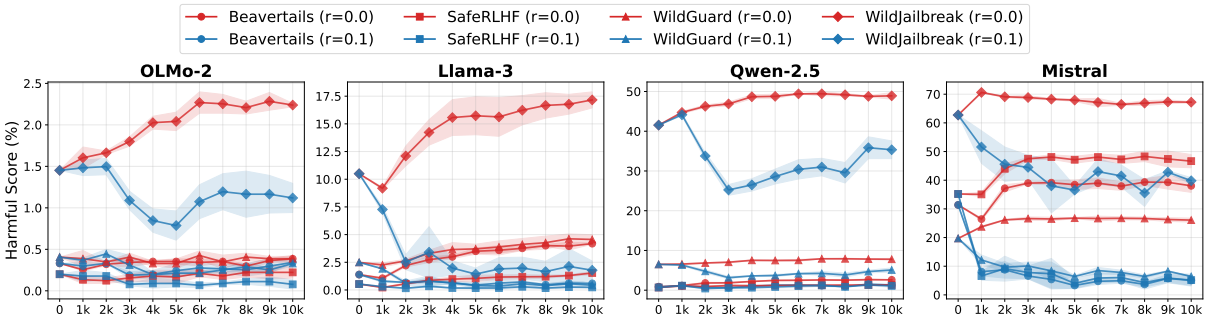

Figure 4: Training dynamics on HellaSwag across models. Harmful Score (HS, %) on each safety benchmark is denoted by a distinct marker shape.

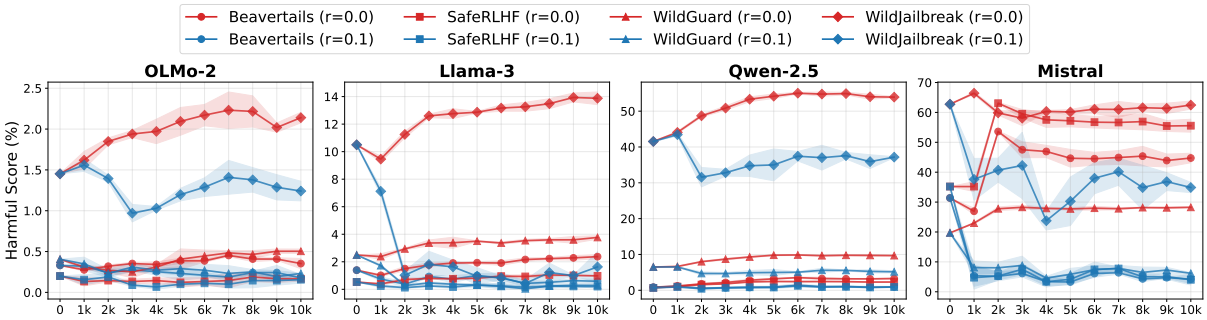

Figure 5: Training dynamics on WinoGrande across models. Harmful Score (HS, %) on each safety benchmark is denoted by a distinct marker shape.

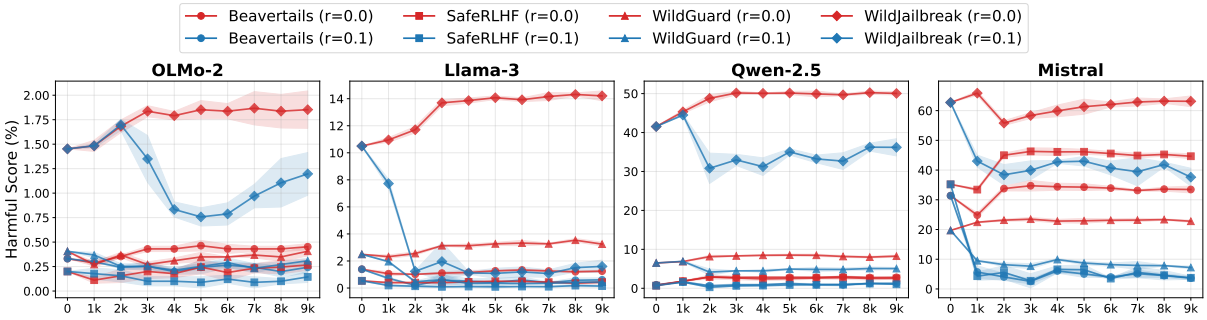

Figure 6: Training dynamics on MedQA across models. Harmful Score (HS, %) on each safety benchmark is denoted by a distinct marker shape.

Table 6: Standard deviations (std) for Harmful Scores (HS, %) and Downstream Task Accuracy (Acc, %) for the comparison of alignment data sources with a mixing ratio of $r = 0.1$. Corresponding to Table 1.

Model	Align Data	GSM8K		MATH		Hellaswag		Winogrande		MedQA		AVG. HS
		HS	Acc	HS	Acc	HS	Acc	HS	Acc	HS	Acc	
OLMo2	None	0.03	0.61	0.07	0.31	0.03	0.72	0.03	0.09	0.07	0.27	0.05
	Aegis	0.15	0.39	0.15	0.68	0.83	0.20	0.61	0.36	0.26	0.27	0.40
	Beavertails	0.50	0.73	0.19	0.33	1.26	0.14	0.67	0.33	0.30	0.24	0.58
	Original	0.04	0.90	0.08	0.27	0.11	0.32	0.13	0.60	0.12	0.91	0.10
	GR-SAP (Ours)	0.04	0.59	0.03	0.14	0.04	0.17	0.01	0.16	0.08	0.40	0.04
Llama3	None	0.50	0.19	0.06	0.49	0.38	0.03	0.19	0.55	0.12	0.43	0.25
	Aegis	4.64	0.95	1.39	0.69	0.79	0.25	0.81	0.82	2.61	0.39	2.05
	Beavertails	2.10	1.31	2.51	0.97	3.01	0.18	2.26	0.78	0.84	0.45	2.14
	GR-SAP (Ours)	0.19	1.08	0.18	0.52	0.32	0.17	0.43	0.24	0.16	0.88	0.26
Qwen2.5	None	0.12	0.72	0.28	0.78	0.32	0.13	0.09	0.67	0.23	0.56	0.21
	Aegis	1.97	0.18	2.62	0.19	2.09	0.08	4.99	0.46	3.25	0.14	2.98
	Beavertails	1.54	0.65	0.27	0.20	2.55	0.25	1.40	0.73	5.20	0.73	2.19
	GR-SAP (Ours)	0.27	0.61	0.34	0.36	0.91	0.15	0.06	0.33	0.78	0.24	0.47
Mistral	None	0.25	2.11	0.24	0.42	1.67	0.24	0.95	0.94	1.13	0.24	0.85
	Aegis	6.25	0.73	0.99	0.66	3.80	0.24	1.22	0.48	2.68	1.70	2.99
	Beavertails	1.95	1.67	2.68	0.14	1.46	0.19	1.36	16.95	2.05	0.24	1.90
	GR-SAP (Ours)	1.43	2.92	0.61	0.92	0.85	0.38	1.25	8.49	1.22	3.75	1.07

Table 7: Standard deviations for MAUVE scores ($\in [0, 1]$) measuring semantic similarity between listed datasets and the original alignment dataset reference. Corresponding to Table 3.

Dataset	Query	Response
AEGIS	0.0086	0.0021
Beavertails	0.0053	0.0036
SafeRLHF	0.0015	0.0018
Open Source AVG.	0.0052	0.0025
GR-SAP (Ours)	**0.0031**	**0.0067**

Table 8: Standard deviation of Harmful Scores (HS, %) and Downstream Task Accuracy (Acc, %) for the comparison of post-processing pipeline with a mixing ratio of $r = 0.1$. Corresponding to Table 2.

Model	Added Filter	GSM8K		MATH		Hellaswag		Winogrande		MedQA		AVG. HS
		HS	Acc	HS	Acc	HS	Acc	HS	Acc	HS	Acc	
OLMo2	raw data	0.02	0.32	0.05	0.39	0.07	0.21	0.05	0.89	0.04	0.89	0.05
	↪+ ppl	0.05	0.80	0.06	0.21	0.05	0.09	0.04	0.37	0.02	0.34	0.05
	↪+ deduplicate	0.03	0.16	0.01	0.25	0.04	0.12	0.12	0.87	0.05	0.30	0.06
	↪+ domain	0.05	0.87	0.01	0.24	0.06	0.08	0.08	0.28	0.06	0.67	0.06
	↪ + exclusion	0.08	0.38	0.02	0.35	0.04	0.23	0.04	0.48	0.07	1.23	0.05
	↪ + revision	0.04	0.59	0.03	0.14	0.04	0.17	0.01	0.16	0.08	0.40	0.05
Llama3	raw data	0.27	0.62	1.06	0.16	0.75	0.16	0.79	0.33	0.47	0.25	0.72
	↪+ ppl	1.42	0.85	0.61	0.06	0.18	0.12	0.86	0.36	0.21	0.59	0.80
	↪+ deduplicate	1.35	1.08	0.76	0.47	0.44	0.33	0.52	0.78	0.97	0.68	0.87
	↪+ domain	1.86	1.16	0.46	0.82	0.05	0.07	0.51	0.21	0.62	0.71	0.93
	↪ + exclusion	1.19	0.64	0.31	0.12	0.49	0.23	1.01	0.64	0.90	0.42	0.85
	↪ + revision	0.19	1.08	0.18	0.52	0.32	0.17	0.43	0.24	0.16	0.88	0.28