Mix Data or Merge Models? Balancing the Helpfulness, Honesty, and Harmlessness of Large Language Model via Model Merging

Jinluan Yang[1], **Dingnan Jin**[2], **Anke Tang, Li Shen, Didi Zhu**[1], **Zhengyu Chen**[1]
Ziyu Zhao[1], **Daixin Wang**[2] **Qing Cui**[2], **Zhiqiang Zhang**[2],**Jun Zhou**[2]
Fei Wu[1],**Kun Kuang**[1*]
[1] Zhejiang University; [2] Ant Group
`yangjinluan@zju.edu.cn`,

Abstract

Achieving balanced alignment of large language models (LLMs) in terms of Helpfulness, Honesty, and Harmlessness (3H optimization) constitutes a cornerstone of responsible AI. Existing methods like data mixture strategies face limitations, including heavy reliance on expert knowledge and conflicting optimization signals. While model merging offers parameter-level conflict-resolution strategies through integrating specialized models' parameters, its potential for 3H optimization remains underexplored. This paper systematically compares the effectiveness of model merging and data mixture methods in constructing 3H-aligned LLMs for the first time, revealing previously overlooked collaborative and conflict relationships among the 3H dimensions and discussing the advantages and drawbacks of data mixture (*data-level*) and model merging (*parameter-level*) methods in mitigating the conflict for balanced 3H optimization. Specially, we propose a novel **R**eweighting **E**nhanced task **S**ingular **M**erging method, **RESM**, through outlier weighting and sparsity-aware rank selection strategies to address the challenges of preference noise accumulation and layer sparsity adaptation inherent in 3H-aligned LLM merging. Extensive evaluations can verify the effectiveness and robustness of RESM compared to previous data mixture (2%-5% gain) and model merging (1%-3% gain) methods in achieving balanced LLM alignment.

1 Introduction

Large language models (LLMs) have demonstrated remarkable capabilities across diverse natural language processing tasks [1–3]. However, their reliable deployment necessitates balanced optimization across three critical dimensions: *Helpfulness* (providing accurate and task-aligned responses), *Honesty* (avoiding hallucinations and misinformation), and *Harmlessness* (preventing toxic or unethical outputs), collectively termed *3H optimization* [4–7]. While recent alignment techniques such as constitutional AI [8], reinforcement learning from human feedback (RLHF) [9], and Direct Preference Optimization (DPO) [10] have improved individual aspects of 3H, seeking a balance remains a significant challenge. For instance, models optimized for helpfulness may inadvertently generate harmful content [11],

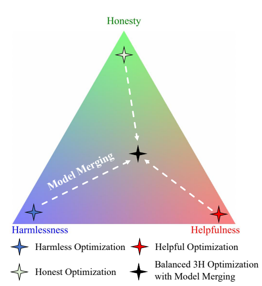


Figure 1: Illustration of trade-offs in optimizing LLMs across the 3H objectives.

[*]Corresponding Authors.

while harmlessness alignment can lead to dishonest responses [12]. This trade-off is illustrated in Figure 1, highlighting the need for systematic approaches to harmonize 3H objectives.

Traditional methods for enhancing 3H properties often rely on *data mixing* strategies assisted by empirically heuristic rules [13], multi-dimensional scoring via reward models [14], or alignment conflict metrics [15], where diverse datasets are combined to fine-tune a single model. While effective, these approaches face practical limitations: (i) data curation requires substantial domain expertise and computational resources [11, 16], and (ii) conflicting optimization signals during fine-tuning may complicate prioritization of alignment objectives without compromising others [15, 17]. As a cost-effective alternative, model merging has gathered great attention for LLM alignment through integrating parameters from specialized aligned models, addressing key challenges such as catastrophic forgetting after fine-tuning [18] and achieving robust reward models [19, 20]. However, for 3H optimization, the effectiveness and limitations of existing merging methods remain underexplored, especially considering the preference noise [21] and layer significance [22, 23] for LLM multi-objective alignment. While preliminary investigations exist [24], these are narrowly focused on constrained scenarios (e.g., multilingual) or employ partial evaluations of 3H dimensions [25] without systematic comparisons. This raises the central question to be explored:

> *Can we benchmark the model merging and data mixing techniques in 3H optimization for LLM alignment and explore the overlooked optimization principles specific to model merging?*

To address this question, we first establish a benchmark for 3H optimization in LLM alignment and systematically compare model merging and data mixing techniques for 3H optimization. Based on this benchmark, we reveal previously overlooked collaborative and conflicting relationships among the 3H dimensions and discuss the advantages and limitations of data mixture (data-level) and model merging (parameter-level) methods in mitigating conflicts for balanced 3H optimization. Additionally, we address the challenges of preference noise accumulation and layer sparsity adaptation in LLM multi-objective merging, proposing a novel reweighting-enhanced task singular merging (RESM) method via outlier weighting and sparsity-aware rank selection to further enhance balanced LLM alignment. In summary, our key contributions are as follows:

• We create the first benchmark for 3H optimization in LLM alignment and systematically compare model merging and data mixing, including our investigations into 15 representative methods (12 training-free model merging methods and 3 representative data mixture methods), 10 preference datasets associated with 5 annotation dimensions, 2 classific LLMs families, and 2 training settings.
• We reveal a range of previously overlooked optimization principles and insights for 3H optimization in LLM alignment. These include: different collaborative and conflict relationships among 3H dimensions, the superiority of model merging over data mixture methods, and the factors affecting the effect of model merging considering redundant parameters updates during post-training.
• Beyond holistic evaluation of existing model merging methods, we propose a novel reweighting-enhanced task singular vector merging algorithm adapted to the preference noise accumulation and layer sparsity during merging through outlier weighting and sparsity-aware rank selection. Extensive experiments verify its effectiveness in achieving balanced LLM alignment.

2 Related Work

Model Merging for LLM Alignment. Model merging has emerged as a parameter-level cost-effective technique for LLM alignment [18], addressing challenges across four aspects: (a) *Stabilizing reference policies* focuses on the over-optimization problems during the RL training. Weight-space averaging of models with varying initializations constructs robust policy ensembles [26], while dynamic trust-region updates [27] and online gradient fusion [28] help preserve foundational capabilities. (b) *Cross-model capability transfer* resolves architectural mismatches during knowledge fusion [29] through probabilistic token alignment [30], vertical domain adaptation [31], and subspace projection [32]. But persistent toxic parameter propagation [33, 34] remains a critical barrier, inducing biased representation transfer during integration. (c) *Avoiding forgetting after finetuning* develops gradient-aware selective merging [35], heterogeneous layer-wise merging [36, 37], and subspace-based merging [38] to mitigate the alignment tax or realign the model after fine-tuning for downstream tasks. (d) *Balancing multi-optimized objectives* employs linear interpolation of reward-tuned models

[39, 17, 19, 20] and Mixture of Experts (MoE) based expert routing [25] to approximate Pareto frontiers but lacks theoretical guarantees for subspace conflict analysis. Additionally, while location-based merging [40] identifies alignment-specific weights, its efficacy is heavily data-dependent. Notably, [24] provides preliminary insights into safety-utility trade-offs in cross-lingual scenarios, but none of these studies explore model merging's potential and limitations for 3H optimization.

Data Mixture for LLM Alignment. Compared with the pretraining data mixture in terms of different domains, LLM alignment aims to achieve a good trade-off between Helpfulness, Honesty, and Harmlessness (3H) regarding human preference [41–43, 7]. (a) *Empirical Methods* [44, 45] have explored the heuristic mixture strategies between helpful and safety-related data to mitigate the safety-utility. (b) *Reward Model-based Methods* train traditional Bradley-Terry models [46, 47] and multi-objective reward models, which are designed to score the data for capturing the complicated human preferences [48–51]. ArmoRM [14] is a representative development aiming to promote LLMs aligned with human-interpretable multi-objective demands like honesty and helpfulness. (c) *New Metric Methods* are initially designed to select preference data only from the quality and diversity dimensions [52, 53], Hummer [15] recently quantifies the conflict among preference datasets to balance diverse alignment objectives effectively. Different from these works that resolve the conflict from the data mixture perspective, we explore the parameter-level model merging solutions and select representative data mixture methods as comparisons to discuss their effectiveness.

3 Revisting Model Merging for Multi-Object Alignment Optimization

3.1 Preliminaries

The intersection of model merging and alignment optimization presents unique challenges and opportunities that warrant dedicated investigation [19, 20]. Given multiple models parameterized by $\theta^1, \theta^2, \cdots, \theta^n$, where each optimizes base model θ^0 towards a different alignment objective, the alignment task vector set can be achieved by $\Delta = (\Delta^1, \cdots, \Delta^n) = (\theta^1 - \theta^0, \cdots, \theta^n - \theta^0)$. Existing merging methods related to LLM multi-objective alignment [18] can be concluded as follows.

Linear interpolation methods, such as Rewarded Soups [17] and Weight Average based methods (WARM [19] and WARP [20]), have demonstrated that simple weighted averaging of model parameters can be effective in learning the Pareto frontier of multiple objectives or achieving robust reward models and reward policies. The merged model can be achieved through: $\theta_{\text{merged}} = \sum_{i=1}^{n} w_i \theta^i$, where the $w = (w_1, w_2, \cdots, w_n)$ is defined as the interpolation weight related to adjustable preference.

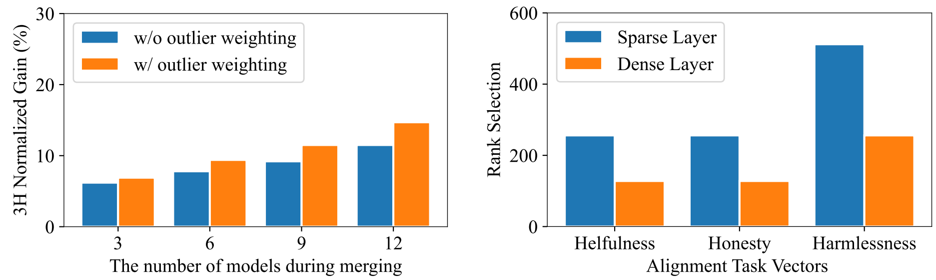
Task-Vector (TV) based methods [54] integrate different parameter update directions (the alignment task vector $\Delta^i = \theta^i - \theta^0$) rather than full model parameters like linear interpolation. Advanced merging approaches like TIES [55], DARE [56], Breadcrumbs [57], and DELLA [58] explore many nuanced ways to identify and preserve crucial subspaces that capture different objectives and resolve the objective conflicts. In general, these methods can be expressed as $\theta_{\text{Merged}} = \theta^0 + \sum_{i=1}^{n} w_i m_i \odot (\theta^i - \theta^0)$, where $m_i \in \{0, 1\}^{|\theta|}$ is a binary mask and $\odot$ is the element-wise multiplication. Moreover, Model stock [59] identifies that model performance correlates strongly with proximity to the center of the weight space and proposes to approximate this optimal center point geometrically.

Task Singular Vector (TSV) based methods [60–62] point out that the *element-wise* mask often breaks the inherent row–column correlations in the weight matrix, potentially destroying a low-dimensional structure of the fine-tuned parameters critical for individual tasks. As an alternative, they exploit the low-rank structure of task vectors through *layer-wise* parameter conflict analysis. By performing Singular Value Decomposition (SVD) with low-rank approximation on top-k singular components of layer-wise task vectors, we can achieve compressed or truncated task matrix through $\text{SVD}_k(\theta_l^i - \theta_l^0) = \boldsymbol{U}_l^{(i)}[:, : k_{\text{fixed}}] \boldsymbol{S}_l^{(i)} \boldsymbol{V}_l^{(i)\top}[: k_{\text{fixed}}, :]$, where U, S, and V are the left singular vectors, singular values, and right singular vectors, the k_{fixed} represents the top-k selection of singular values.

$$\min_{\boldsymbol{U}_{l\perp}} \|\boldsymbol{U}_{l\perp} - \boldsymbol{U}_l\|_F \quad \text{s.t.} \quad \boldsymbol{U}_{l\perp}^\top \boldsymbol{U}_{l\perp} = \boldsymbol{I}, \tag{1}$$

$$\min_{\boldsymbol{V}_{l\perp}} \|\boldsymbol{V}_{l\perp} - \boldsymbol{V}_l\|_F \quad \text{s.t.} \quad \boldsymbol{V}_{l\perp}^\top \boldsymbol{V}_{l\perp} = \boldsymbol{I}, \tag{2}$$

$$\theta_{\text{Merged Layer}} = \theta_l^0 + \sum_{i=1}^{n} \boldsymbol{U}_{l\perp}^{(i)}[:, : k_{\text{fixed}}] \boldsymbol{S}_l^{(i)} \boldsymbol{V}_{l\perp}^{(i)\top}[: k_{\text{fixed}}, :]. \tag{3}$$



(a) Preference Noise Accumulation (b) Effective Rank Analysis

Figure 2: (a) illustrates the impact of outlier weighting in model merging when incorporating multi-aligned models. The performance discrepancy before and after processing quantifies the degree of preference noise accumulation; (b) depicts the effective rank required to capture 95% of the total energy in singular values for task vectors derived from 3H training. Larger ranks indicate the necessity of retaining a higher proportion of singular values to preserve task-relevant information.

Assisted by decorrelat-based whitening transformation as Eq.(1) and Eq.(2), we can obtain orthogonal singular vectors $\boldsymbol{U}_{l\perp}$ and $\boldsymbol{V}_{l\perp}$ to mitigate the interference among task matrices. Finally, the layer-wise weight for the merged model can be defined as Eq.(3), where the w_l is the scaling factor.

3.2 Motivation

Despite the successes of TSV-based methods outlined above, several overlooked challenges undermine the efficacy of model merging for 3H optimization:

(i) Negative Outliers from Preference Noise Accumulation: The core design of previous merging methods is to separate task-specific and task-shared parameters through element-wise mask or layer-wise SVD decomposition [18]. But all of these works ignore the preference noise accumulation [21], which is a special problem for LLM alignment, especially when more alignment objectives or models are considered during merging. This introduces additional outlier weight updates that make it difficult to capture true task-specific optimization direction, so as to weaken the effect of conflict resolution.

As shown in the Figure 2a, we respectively train models for each dimension of 3H optimization. The merging results with 3/6/9/12 models represent that for 3H optimization, we respectively select 1/2/3/4 single-dimension models with different hyperparameters. We apply the 3σ principle to mask the outlier weight for singular value parameter updates (the details can be shown in Section 4) while adopting the representative task-singular vector merging algorithm, TSVM [60]. From the results, we can find that masking the outlier weight within the singular value S can strengthen the merging effect, and the accumulation preference noise has the same trend as the increased model numbers.

(ii) Unreasonable Fixed Rank Selection for Each Layer: Conventional model merging methods employ a uniform rank selection threshold k across all layers, failing to account for layer-specific sparsity patterns and parameter importance heterogeneity in LLMs. As evidenced by layer-wise analyses [63], sparse attention activation and dense feed-forward layers exhibit fundamentally different sparsity characteristics. Moreover, recent mechanistic studies [23, 64, 22] reveal that alignment capabilities predominantly emerge from localized parameter updates in specific subnetwork regions rather than global changes. Both of them necessitate distinct rank selection strategies during merging.

As shown in the Figure 2b, we display the difference in the rank selection between dense and sparse layers while keeping 95 percent of information/energy within the singular value [65]. This divergence of rank among layers highlights the challenge of using a fixed top-k selection to compress the rank for model merging as Eq.(3), because we may either discard important components or keep unnecessary components that cause interference between different alignment objectives.

4 Reweighting-Enhanced Task Singular Vector Merging for 3H Optimization

Overall: Based on the above analysis, we propose a novel **R**eweighting **E**nhanced task **S**ingular vector **M**erging algorithm (RESM), with theoretical foundations in outlier detection and layer-wise sparsity analysis for rank selection, aiming to improve model merging for 3H optimization. Thus, we can transform Eq.(3) to Eq.(4) by integrating with reweighting-based optimization. The full framework of RESM can be shown in Algorithm 1.

$$\boldsymbol{\theta}_l^{\text{RESM}} = \boldsymbol{\theta}_l^0 + \sum_{i=1}^{n} \underbrace{\boldsymbol{U}_{l\perp}^{(i)}[:, :k_l]}_{\substack{\text{Adaptive}\\\text{Rank Selection}}} \underbrace{\left(\alpha_l^{(i)} \boldsymbol{S}_l^{(i)}\right)}_{\substack{\text{Outlier-Aware}\\\text{Weighting}}} \underbrace{\boldsymbol{V}_{l\perp}^{(i)\top}[:k_l, :]}_{\substack{\text{Adaptive}\\\text{Rank Selection}}}, \tag{4}$$

To address (i), compared with directly utilizing full singular values, we employ layer-wise outlier detection to aggregate the Outlier-Aware Weight for reweighting the singular values. This means we should check which parts of the singular values can truly represent the optimization direction towards the alignment process. Considering the heavy-tailed distribution of LLM parameter updates, where few parameters undergo significant changes while most exhibit minor adjustments, we leverage the 3σ principle, which aligns with this characteristic. Thus, we adopt statistical significance filtering to weaken the noise effect and normalize competitive weight to identify true optimization adjustments. The $\Delta_{l,r,c}^{(i)} \in \mathbb{R}$ denotes the weight deviation at row r, column c of layer l for model i relative to initial model, $\mu_r^{(i)}$ and $\sigma_r^{(i)}$ represent the mean (Eq.(5)) and standard deviation of deviations (Eq.(6)) in row r, quantifying central tendency and dispersion, $\alpha_l^{(i)} \in [0,1]$ (Eq.(7)) computes layer-wise aggregation weights via L_1-normalized sparse outlier magnitudes, and $\textsc{Threshold}(\boldsymbol{M}, \tau)$ applies hard-thresholding to suppress elements in matrix $\boldsymbol{M}$ with absolute values below τ.

$$\mu_{l,r}^{(i)} = \mathbb{E}_c[|\Delta_{l,r,c}|], \tag{5}$$

$$\sigma_{l,r}^{(i)} = \sqrt{\mathbb{E}_c[|\Delta_{l,r,c}|^2] - (\mu_{l,r}^{(i)})^2}, \tag{6}$$

$$\alpha_l^{(i)} = \frac{\sum\limits_{r=1}^{d_l} \|\text{Threshold}(\boldsymbol{\Delta}_{l,r,:}^{(i)}, \mu_{l,r}^{(i)} + 3\sigma_{l,r}^{(i)})\|_1}{\sum\limits_{j=1}^{n}\sum\limits_{r=1}^{d_l} \|\text{Threshold}(\boldsymbol{\Delta}_{l,r,:}^{(j)}, \mu_{l,r}^{(j)} + 3\sigma_{l,r}^{(j)})\|_1} \tag{7}$$

Our outlier-aware reweighting mechanism operates through two complementary mechanisms: *Noise Suppression*: By thresholding parameter deviations via the 3σ rule, we filter out low-magnitude fluctuations that predominantly encode noise, forcing the singular vectors $\boldsymbol{u}_r^{(i)}$ to align with statistically significant task features; *Task Equilibrium*: The layer-wise aggregation weights $\alpha_l^{(i)}$ are globally normalized across all models, ensuring balanced contributions from diverse tasks and preventing dominance by high-magnitude updates that may obscure subtle yet critical features. More details for outlier-aware weighting for singular value can be shown in Appendix A.1.

To address (ii), instead of fixed top-k strategy, we propose to adaptively decide the level of rank selection based on the layer sparsity. We can first compute the sparsity consensus for all models as Eq.(8) and then achieve the dynamic rank as Eq.(9), where $\gamma_0 > 0$ and $\gamma > 0$ control the base rank and sparsity-related rank reduction respectively, the k_l is defined as the dynamic rank for layer l determined by sparsity Ω_l. We set $\gamma_0 = 0.2$, $\gamma = 0.6$ and $\epsilon = 0.1$ by default. We can observe that for layers with high sparsity ($\Omega_l \to 1$), the optimal rank selection $\Omega_l \to d_l(\gamma_0 + \gamma\Omega_l)$ retains most singular, whereas for dense layers $\Omega_l \to 0$, the rank k_l decreases significantly, inducing stronger dimensionality reduction through truncation.

$$\Omega_l = \frac{1}{nd_l^2} \sum_{i=1}^{n} \sum_{r,c=1}^{d_l} \mathbb{I}\left(|\Delta_{l,r,c}^{(i)}| < \epsilon\right) \tag{8}$$

$$k_l = \lfloor d_l(\gamma_0 + \gamma\Omega_l) \rfloor \tag{9}$$

Our sparsity-adaptive rank selection mechanism operates through two complementary principles: *Information Preservation*: For dense layers, where parameter updates demonstrate relatively uniform distributions with predominantly small adjustments, employing lower-rank approximations proves effective for noise suppression while preserving principal components. However, this necessitates

Algorithm 1: Reweighting-Enhanced Task Singular Vector Merging

Input : Initial model $\boldsymbol{\theta}^0$ and Further Aligned models $\{\boldsymbol{\theta}^i\}_{i=1}^n$ with same layers L, Sparsity factor $\gamma \in [0,1]$, $\epsilon > 0$

Output: Merged model $\boldsymbol{\theta}^*$

for *layer* $l \leftarrow 1$ **to** L **do**

```
// Step1:Alignment Task Vector Extraction
```

$\boldsymbol{\Delta}_l^{(1:n)} \leftarrow [\boldsymbol{\theta}_l^i - \boldsymbol{\theta}_l^0]_{i=1}^n$

```
// Step2:Outlier-Aware Weighting
```

for *model* $i \leftarrow 1$ **to** n **do**

Compute row-wise statistics: $\boldsymbol{\mu}_l^{(i)}, \boldsymbol{\sigma}_l^{(i)} \leftarrow \textsc{RowOutlierScore}(|\boldsymbol{\Delta}_l^{(i)}|)$

Calculate sparse aggregation weights:

$\alpha_l^{(i)} \leftarrow \frac{\sum_{r=1}^{d_l} \|\textsc{Threshold}(\boldsymbol{\Delta}_{l,r,:}^{(i)}, \mu_{l,r}^{(i)} + 3\sigma_{l,r}^{(i)})\|_1}{\sum_{j=1}^{n}\sum_{r=1}^{d_l} \|\textsc{Threshold}(\boldsymbol{\Delta}_{l,r,:}^{(j)}, \mu_{l,r}^{(j)} + 3\sigma_{l,r}^{(j)})\|_1}$

```
// Step 3:  Sparsity-Adaptive Rank Selection
```

Compute layer sparsity consensus: $\Omega_l \leftarrow \frac{1}{nd_l^2}\sum_{i=1}^{n}\sum_{r,c=1}^{d_l} \mathbb{I}(|\Delta_{l,r,c}^{(i)}| < \epsilon)$

Determine dynamic rank: $k_l \leftarrow \lfloor d_l(\gamma_0 + \gamma\Omega_l) \rfloor$

```
// Step 4:Reweighting Optimization during Merging
```

for *model* $i \leftarrow 1$ **to** n **do**

Decompose: $[\boldsymbol{U}_l^{(i)}, \boldsymbol{S}_l^{(i)}, \boldsymbol{V}_l^{(i)}] \leftarrow \mathrm{SVD}(\boldsymbol{\Delta}_l^{(i)})$

Compute orthogonal projections $\boldsymbol{U_l}_{\perp}^{(i)}$ and $\boldsymbol{V_l}_{\perp}^{(i)}$ via Eq.(1) via Eq.(2)

Reweight for Outlier Weight: $\boldsymbol{S}_l^{(i)} \leftarrow \alpha_l^{(i)} \cdot \boldsymbol{S}_l^{(i)}$

Reweight for Rank Selection: $\boldsymbol{U_l}_{\perp}^{(i)} \leftarrow \boldsymbol{U_l}_{\perp}^{(i)}[:, : k_l]$, $\boldsymbol{V_l}_{\perp}^{(i)} \leftarrow \boldsymbol{V_l}_{\perp}^{(i)}[: k_l, :]$, $\boldsymbol{S}_l^{(i)} \leftarrow \boldsymbol{S}_l^{(i)}[: k_l, : k_l]$

Merge Components: $\boldsymbol{M}_l \leftarrow \sum_{i=1}^{n} \boldsymbol{U_l}_{\perp}^{(i)} \boldsymbol{S_l}^{(i)} \boldsymbol{V_l}_{\perp}^{(i)\top}$

Update the Layer for the Merged Model: $\boldsymbol{\theta}_l^* \leftarrow \boldsymbol{\theta}_l^0 + \boldsymbol{M}_l$

careful determination of the optimal rank selection threshold to balance between information retention and noise elimination. Conversely, sparse layers display concentrated parameter updates along a few dominant directions, potentially containing critical outlier components. Here, maintaining a higher rank becomes essential to ensure the preservation of these salient directional features, thereby preventing substantial information loss through excessive rank truncation. *Conflict Mitigation*: By preserving dominant singular directions in sparse layers and enforcing orthogonality through Eq.(1), we reduce overlaps between task-specific parameters, decoupling interference-prone optimization trajectories. More details about rank selection can be shown in Appendix A.2.

5 Experiments

5.1 Experimental Setup

Datasets: As shown in Table 1, we select commonly used preference data for model training. These datasets can be categorized into five groups from the annotation perspective.

Table 1: Dataset statistics for our DPO training.

Annotation Perspective	Dataset	Judge
Helpfulness	HelpSteer [49]	GPT4-Turbo
	Py-Dpo [66]	GPT4-Turbo
	Distilabel-Orca [67]	GPT4-Turbo
	Distilabel-Capybara [68]	GPT4-Turbo
Harmlessness	UltraSafety [5]	GPT4-Turbo
Honesty	Truthy-Dpo-v0.1 [69]	Human
	GRATH [70]	Llama2
Helpfulness&Honesty	UltraFeedback [52]	GPT4-Turbo
Helpfulness&Harmlessness	PKU-Safe-RLHF [11]	GPT4-Turbo
	Nectar [71]	GPT4-Turbo

Backbones: Following SimPO [72], we adopt two instruction-tuned models: Llama-3-8B-Instruct [73] and Mistral-7B-Instruct-v0.2 [74]. These serve as the SFT model, and we then perform DPO training on the full network using the preference data.

Baselines:(i) Individual Training: We respectively train one model for each annotation perspective as stated by Table 1. These models are saved for model merging. **(ii) Mixture Training**: We adopt the full datasets shown in Table 1 and then adjust the data mixture proportion before training based on the *Empirical* methods [44, 45], the multi-dimension score of the Reward model *ArmoRM-Llama3-8B* [14] and the alignment conflict metric from *Hummer* [15]. The implementation details can be shown in Appendix C;**(iii) Model Merging:** Considering that the constraints of data availability and test data leak will limit the generalization of merging methods for LLMs, we mainly adopt *training-free multi-task or multi-object alignment* merging strategies from MergeKit [75], which includes Weight Average [76], Task Arithmetic [54], Ties-Merging [55], DARE[56], DELLA [58], Model Stock [59] and Model Breadcrumbs [57]. Moreover, from the perspective of Pareto-optimal front [39, 17, 19, 20] and singular vector decomposition [60, 61], we select Rewarded Soup [17], TSVM [60] as two additional training-free merging methods for 3H optimization. We provide discussions about training-based and MOE-based merging methods [25] in Appendix B.

Settings: We construct two different settings to verify the effectiveness of model merging for 3H optimization: **(i) Static Optimization for DPO Training at once** as Table 3 and Table 4, where we aim to achieve an aligned model that simultaneously meets the 3H demands using various annotated preference data at once. **(ii) Continual Optimization for Sequential DPO Training** as Table 10 and Table 11, which refers to the continual and dynamic circumstances with newly curated preference data and more customized demands compared to previously trained models. In this case, we need to simultaneously focus on the effectiveness and efficiency of constructing an aligned model.

Evaluation: (i) For Helpfulness: we select Math, GSM8K, ARC-C, ARC-E, MMLU, MBPP-Plus, HumanEval-Plus [77], and MT-Bench [78] to asses the helpfulness of LLMs; **(ii) For Honesty:** we utilize the HaluEval-Wild [79] for evaluating honesty or hallucinations; **(iii) For Harmlessness:**, we conduct safety-related (SaladBench [80]) and refusal-related (OR-Bench [81]) evaluations to measure the harmlessness of models. Higher values are preferred for all reported results to ensure the reasonableness and fairness of evaluation. The *normalized metric* is calculated based on the relative gain of each dimension to avoid the imbalanced evaluation datasets for the 3H perspective. More details can be shown in the Appendix C.2.

Table 2: Necessary specifications for the strategy and scaling of each method.

Method	Strategy	Scaling
Data Mixture-Based Methods		
Heuristic [13]	Empirically heuristic-adjusted ratio	Data Mixture Ratio
ArmoRM [14]	Reward Model	Multi-object Data Selection
Hummer [15]	Alignment Conflict Metric	Multi-object Data Selection
Merging-Based Methods		
Weight Average [76]	Linear Int. Consensus	Parameter Weight Coeff.
Rewarded Soup [17]	Linear Int. Consensus	Parameter Weight Coeff.
Task Arithmetic [54]	Linear Int. Consensus	Parameter Scaling Factor
Ties [55]	Top-k Sparsification	Parameter Scaling Factor
DARE [56]	Random Sparsification	Parameter Scaling Factor
DELLA [58]	Random Sparsification	Parameter Scaling Factor
Breadcrumbs [57]	Top/Bottom-k Sparsification	Parameter Scaling Factor
Model Stock [59]	Geometric Sparsification	Parameter Adaptive Ratio
TSVM [60]	Singular Value Decomposition	Parameter Scaling Factor

5.2 Experimental Results

There exist different collaborative and conflict relationships in terms of 3H objectives for LLM alignment. As shown in Figure 3, we display the trade-off through individual training comparison. Denote the results of Instruct LLMs as the grey line in the Figure, we can compare the results of Honesty and Helpfulness after performing individual Helpful, Honest, and Harmless Training to distinguish the relationship between each optimization dimension. From the results, we can observe that there exist different collaborative and conflict relationships between helpfulness, honesty, and harmlessness while performing DPO Training, exhibiting that Helpful Training benefits 3H performance simultaneously, but Honest and Harmless Training weaken each other.

Model merging can serve as a good alternative for data mixture methods in mitigating the 3H conflict. As shown in Table 3 and Table 4, we compare the effectiveness of data mixture and model merging methods for 3H optimization of Llama3 [73] and Mistral [74]. *For data mixture methods*, they mitigate the 3H conflict by collecting full training preference data and then filtering conflict samples. Compared with heuristic strategies and reward model based strategies, which rely on historical training data and human effort, Hummer is specially designed for evaluating conflict for full training preference data, which can achieve better 3H results with a norm gain from 7.68% to 10.16% on the Llama3. *For model merging methods*, compared with full training strategies, they advocates for phased optimization to negotiate competing alignment objectives through *dimension-specific individual training*, where we first conduct individual training to obtain models for five different annotation dimensions respectively, and then adopt *conflict-aware parameter merging strategies*, such as random sparsification, Top-k filtering, and singular value decomposition, to merge these models into an ideal one that can achieve close or superior results than full training methods. Take the experiment on Llama3 for example, compared with the best data mixture methods, Hummer(10.16%), model

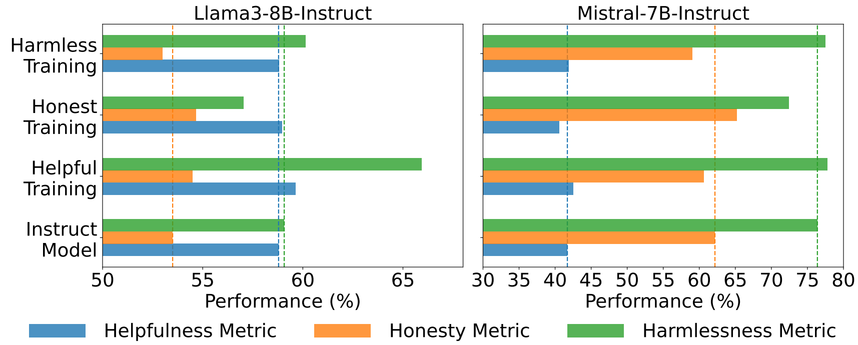


Figure 3: Illustration of the 3H Trade-Off, where Helpful Training benefits 3H performance simultaneously, but Honest and Harmless Training weaken each other. The dashed line (Instruct Model) serves as the reference, where rectangles on the left represent the weakening effect, and vice versa.

Table 3: 3H Results Under Static Optimization Setting where we perform DPO training using various datasets at once. The normalized gain metric is the average value of the relative gain for each dimension compared with the results of Llama3-8B-Instruct.

Methods	Helpfulness								Honesty	Harmlessness		Helpful_Avg	Honest_Avg	Harmless_Avg	Norm_Gain
	Math	GSM8K	ARC-E	ARC-C	MMLU	MBPP_Plus	HumanEval_Plus	MT-Bench	HaluEval_Wild	Salad_Bench	OR-Bench				
llama3-8B-Instruct	28.08	78.09	93.65	82.03	68.20	58.99	53.05	8.25	53.50	91.16	26.97	58.79	53.50	59.07	—
Helpfulness	29.08	79.30	93.65	81.69	68.58	57.94	58.54	8.33	55.00	89.83	42.06	59.64↑1.45%	55.00↑2.80%	65.95↑11.65%	+5.30%
Honesty	28.52	78.77	93.65	81.36	68.34	58.47	54.27	8.45	54.67	92.18	21.95	58.98↑0.32%	54.67↑2.19%	57.07↓3.39%	-0.29%
Harmlessness	28.88	77.33	93.65	82.03	68.32	59.79	52.44	8.15	53.33	92.36	27.92	58.82↑0.05%	53.33↓0.32%	60.14↑1.81%	+0.51%
Helpfulness&Honesty	29.60	77.63	93.47	82.71	68.33	59.79	59.15	8.18	56.00	90.86	39.80	59.86↑1.82%	56.00↑4.67%	65.33↑10.60%	+5.70%
Helpfulness&Harmlessness	30.02	77.26	93.47	82.37	68.31	58.99	56.11	8.16	54.50	90.27	58.86	59.34↑0.94%	54.50↑1.87%	74.57↑26.24%	+9.68%
3H Mixture Full Training (Heurisistic)	28.21	78.85	93.65	81.69	68.38	60.85	57.32	8.48	54.67	92.06	35.36	59.68↑1.51%	54.67↑2.19%	63.71↑7.85%	+3.85%
3H Mixture Full Training (ArmoRM)	28.81	78.97	93.65	82.39	68.42	60.55	58.22	8.52	55.50	92.11	42.12	60.24↑2.47%	55.50↑3.74%	69.02↑16.84%	+7.68%
3H Mixture Training (Hummer)	29.41	78.95	93.65	82.69	68.59	60.41	58.15	8.58	55.60	92.10	50.11	60.35↑2.65%	55.60↑3.93%	73.21↑23.90%	+10.16%
Weight Average	29.80	78.01	93.47	82.71	68.43	59.26	57.32	8.02	57.78	91.72	41.48	59.63↑1.43%	57.78↑8.00%	66.60↑12.75%	+7.39%
Rewarded Soup	29.64	77.94	93.47	82.71	68.54	60.85	57.93	8.32	57.55	90.86	50.08	59.93↑1.94%	57.55↑7.57%	70.47↑19.30%	+9.60%
Model Stock	28.72	78.24	93.47	82.71	68.41	59.79	56.10	8.03	53.00	91.62	32.28	59.43↑1.09%	53.00↓0.93%	61.95↑4.88%	+1.68%
Task Arithmetic	29.02	79.05	93.30	83.39	68.35	57.14	51.83	8.37	57.33	91.39	28.29	58.81↑0.03%	57.33↑7.16%	59.84↑1.30%	+2.83%
Ties	29.30	78.17	93.30	83.05	68.52	56.61	53.05	8.20	54.33	89.13	29.07	58.78↓0.02%	54.33↑1.55%	59.10↓0.05%	+0.49%
DARE	29.42	78.39	93.47	82.71	68.41	59.26	56.71	8.28	57.00	91.85	38.80	59.58↑1.34%	57.00↑6.54%	65.33↑10.60%	+6.16%
DARE Ties	29.64	78.01	93.47	82.71	68.43	59.26	57.32	8.07	56.00	92.16	36.88	59.61↑1.40%	56.00↑4.67%	64.52↑9.23%	+5.10%
DELLA	29.08	78.92	93.30	83.73	68.41	54.76	52.44	8.43	54.67	91.37	63.31	58.63↓0.27%	54.67↑2.19%	77.34↑30.93%	+10.95%
DELLA Ties	29.20	75.97	93.30	83.39	68.46	56.08	49.39	8.16	54.00	87.95	70.02	57.99↓1.36%	54.00↑0.93%	78.99↑33.72%	+11.10%
Breadcrumbs	29.46	77.79	93.30	83.39	68.53	60.85	54.88	8.24	59.33	91.60	44.85	59.56↑1.31%	59.33↑10.89%	68.23↑15.51%	+9.24%
Breadcrumbs Ties	29.72	78.54	93.30	83.05	68.46	60.05	53.66	8.14	55.50	90.00	58.52	59.37↑0.99%	55.50↑3.74%	74.26↑25.72%	+10.15%
TSVM	29.92	77.63	93.12	82.17	68.51	59.26	55.49	8.29	56.20	89.43	67.76	59.30↑0.87%	56.20↑5.05%	78.60↑33.08%	+13.00%
RESM (ours)	29.89	78.77	93.65	82.27	68.41	59.46	56.55	8.29	58.20	89.92	69.27	59.62↑1.41%	58.20↑8.79%	79.60↑34.72%	**+14.97%**

merging methods including DELLA Ties(11.10%), Breadcrumbs Ties(10.15%), TSVM(13.00%) ,and our RESM(14.97%) can consistently achieve comparable or superior results for balanced 3H optimization. These results collectively confirm that model merging's phased optimization paradigm effectively negotiates competing alignment objectives, which provides new insights for addressing the trilemma of 3H optimization for LLM alignment.

The effect of model merging for 3H optimization is closely related to their conflict-resolution strategies. RESM consistently achieves better results due to its reweighting designs. As shown in Table 2, we can divide existing parameter-level strategies into three categories: linear consensus, sparsification, and singular value decomposition. Linear interpolation of full model parameters or task vectors neglects the parameter conflict, limiting their performance for 3H optimization in LLM alignment. The sparsification-based method holds the assumption that pruning redundant (DARE and DELLA) or outlier parameters (Breadcrumbs) that do not represent the direction of updates for task vectors can improve the effect of model merging, but the level of sparsity is difficult to control for LLM through even with different sparsification methods. From the results of Table 3 and Table 4, we can observe that there is no fixed and stable trend for the results of sparsification-based methods due to random sparsification. For example, DELLA-Ties and DARE-Ties exhibit opposite phenomena in Llama3 and Mistral. More details about the sparsity that influences the effect of merging can be shown in Appendix C.4. In contrast, both TSVM and RESM can achieve stable performance gain through decomposed task singular vectors without heavily depending on sparsification. Moreover, our RESM enhances the merging effect of TSVM with a normalized gain from 13.00% to 14.97% due to its reweighting optimization adapted to preference noise accumulation and fixed rank problems.

RESM can achieve robust and efficient 3H optimization in continual LLM alignment than previous methods As shown in Table 10 and Table 11 in the Appendix C.3, we sequentially perform DPO training using data with annotations about Helpfulness&Honesty (Stage1), Helpfulness&Harmlessness (Stage2) and Helpful (Stage3) to simulate continuous optimization in real-world

Table 4: 3H Results Under Static Optimization Setting where we perform DPO training using various datasets at once. The normalized gain metric is the average value of relative gain for each dimension compared with the results of Mistral-7B-Instruct-v0.2.

Methods	Helpfulness								Honesty	Harmlessness		Helpful_Avg	Honest_Avg	Harmless_Avg	Norm_Gain
	Math	GSM8K	ARC-E	ARC-C	MMLU	MBPP_Plus	HumanEval_Plus	MT-Bench	HaluEval_Wild	Salad_Bench	OR-Bench				
Mistral-7B-Instruct-v0.2	9.54	46.17	82.36	72.88	59.97	26.46	28.66	7.55	62.17	78.07	74.68	41.70	62.17	76.38	—
Helpfulness	9.44	47.38	84.48	75.25	60.70	22.49	32.31	7.80	60.60	74.84	80.67	42.48↑1.87%	60.60↓2.52%	77.76↑1.81%	+0.39%
Honesty	9.34	46.63	82.54	71.19	59.04	24.34	23.78	7.76	65.20	83.98	60.82	40.58↓2.69%	65.20↑4.87%	72.40↓5.21%	-1.01%
Harmlessness	9.40	46.10	81.42	72.88	60.03	27.51	30.39	7.43	59.00	85.43	69.54	41.90↑0.48%	59.00↓5.10%	77.49↑1.45%	-1.06%
Helpfulness&Honesty	8.76	43.14	82.01	74.92	59.78	25.93	27.33	7.59	61.33	78.74	77.23	41.18↓1.25%	61.33↓1.35%	77.99↑2.11%	-0.16%
Helpfulness&Harmlessness	9.96	41.77	83.42	75.59	61.13	34.92	29.27	7.46	50.60	79.83	86.05	42.94↑2.97%	50.60↓18.61%	82.94↑8.59%	-2.35%
3H Mixture Full Training (Heurisistic)	9.56	41.70	83.06	74.24	60.23	22.75	34.15	7.69	62.00	81.13	72.97	41.67↓0.07%	62.00↓0.27%	77.05↑0.88%	+0.18%
3H Mixture Full Training (ArmoRM)	9.71	43.70	83.65	74.54	60.33	25.11	33.58	7.75	61.95	81.10	75.55	42.30↑1.44%	61.95↓0.35%	78.32↑2.54%	+1.21%
3H Mixture Training (Hummer)	9.79	44.50	83.72	74.89	60.53	25.85	33.15	7.56	62.05	81.85	75.28	42.50↑1.92%	62.05↓0.19%	78.57↑2.87%	+1.53%
Weight Average	9.86	45.49	82.36	74.58	60.70	27.25	31.10	7.47	60.60	81.51	72.90	42.35↑1.56%	60.60↓2.52%	77.21↑1.09%	+0.04%
Rewarded Soup	9.74	45.11	82.54	74.58	60.65	26.72	30.49	7.48	60.71	81.43	72.51	42.16↑1.10%	60.71↓2.35%	76.97↑0.77%	-0.16%
Model Stock	9.80	46.93	82.36	74.24	60.34	25.13	30.49	7.19	61.81	80.11	73.78	42.06↑0.86%	61.81↓0.58%	76.95↑0.75%	+0.34%
Task Arithmetic	9.76	44.12	84.13	73.90	60.86	27.25	33.54	7.44	61.01	83.91	71.04	42.63↑2.23%	61.01↓1.87%	77.48↑1.44%	+0.60%
Ties	10.22	41.47	85.19	74.92	61.34	27.25	31.10	7.46	58.73	82.15	81.13	42.37↑1.61%	58.73↓5.53%	81.64↑6.89%	+0.99%
DARE	10.10	43.82	84.48	73.90	60.78	27.25	32.93	7.47	61.05	83.80	71.04	42.59↑2.13%	61.05↓1.80%	77.42↑1.36%	+0.56%
DARE Ties	10.10	42.46	85.00	74.58	61.05	26.98	31.71	7.61	59.28	82.28	81.91	42.49↑1.89%	59.28↓4.65%	82.10↑7.49%	+1.58%
DELLA	10.26	42.76	84.83	73.56	60.86	26.19	32.93	7.47	61.00	84.36	77.20	42.35↑1.56%	61.00↓1.88%	77.78↑1.83%	+0.50%
DELLA Ties	10.14	40.71	84.48	75.93	61.56	30.95	32.32	7.40	56.10	82.00	84.27	42.94↑2.97%	56.10↓9.76%	83.14↑8.85%	+0.69%
Breadcrumbs	9.48	43.06	83.60	73.56	60.94	27.25	31.71	7.52	60.20	83.88	70.91	42.14↑1.06%	60.20↓3.17%	77.40↑1.34%	-0.26%
Breadcrumbs Ties	10.20	41.85	85.01	76.61	61.27	26.72	30.49	7.48	60.04	81.83	80.49	42.45↑1.80%	60.04↓3.43%	81.16↑6.26%	+1.54%
TSVM	10.40	44.88	84.29	75.24	60.87	28.50	32.32	7.65	61.10	83.25	78.51	43.02↑3.17%	61.10↓1.72%	80.88↑5.89%	+2.45%
RESM (ours)	10.44	45.00	84.35	75.79	60.87	28.50	32.52	7.71	61.50	84.25	80.25	43.15↑3.48%	61.50↓1.08%	82.25↑7.69%	**+3.36%**

scenarios. Comparative analysis of continual training stages reveals that catastrophic forgetting effects paradoxically enhance large language models' (LLMs) alignment with honesty, helpfulness, and harmlessness (3H) through interactive optimization. Our method strategically initializes model merging from the foundational Instruct checkpoint rather than intermediate checkpoints, thereby eliminating hyperparameter sensitivity in continual DPO training while mitigating overfitting to prior objectives that impede adaptation to new optimization targets. Experimental results demonstrate RESM's superior performance over final-stage models across 3H metrics, confirming its robustness for multi-objective alignment optimization.

RESM can achieve better results than traditional sparse LLM works with outlier-based optimization. While outlier-based optimization can also be used for pruning LLMs [84, 85], they are *two-stage* methods constrained to dealing with the parameters of only one LLM, while we focus on the outlier weights of different LLMs during *end-to-end* model merging. This means we should additionally consider the parameters conflict while merging different LLMs, rather than post-hoc process a well-merged LLM. To further distinguish our contribution, as shown in Table 5, we conduct outlier-related experiments on Llama3, including two representative outlier-based pruning methods, Wanda [82] and Owl [83]. We can observe that RESM can consistently achieve better results.

Table 5: Comparison with other outlier-based LLM works on Llama3.

Method	Helpfulness	Honesty	Harmlessness	Norm_Gain
Llama3-8B-Instruct	58.79	53.50	59.07	–
TSVM	59.30↑0.87%	56.20↑5.05%	78.60↑33.06%	+12.99%
TSVM+Wanda [82]	59.35↑0.95%	56.32↑5.27%	78.75↑33.28%	+13.17%
TSVM+Owl[83]	59.41↑1.05%	56.40↑5.42%	79.15↑33.93%	+13.47%
RESM (ours)	59.62↑1.41%	58.20↑8.79%	79.60↑34.72%	**+14.97%**

Ablation Studies. As shown in Table 6 and Table 7, we can observe that integrating both outlier weighting and sparsity-adaptive rank selection can collectively enhance the merging effect, which can verify the responsibility of our reweighting-based optimization. Notably, RESM outperforms data mixture baselines, achieving a gain of close to 1.5x to 2.1x improvement. These results validate model merging as a viable pathway for LLM alignment towards balancing multi-dimensional objectives

Table 6: Ablation studies for Reweighting-Induced Improvements on Llama3.

Method	Helpfulness	Honesty	Harmlessness	Norm_Gain
Llama3-8B-Instruct	58.79	53.50	59.07	–
Hummer (best mixture)	60.35↑2.65%	55.60↑3.93%	73.21↑23.94%	+10.17%
TSVM (best merging)	59.30↑0.87%	56.20↑5.05%	78.60↑33.06%	+12.99%
RESM w/o Outlier Weighting	59.52↑1.24%	56.20↑5.05%	79.45↑34.51%	+13.60%
RESM w/o Rank Selection	59.45↑1.12%	56.80↑6.17%	79.05↑33.83%	+13.71%
RESM (ours)	59.62↑1.41%	58.20↑8.79%	79.60↑34.72%	**+14.97%**

Table 7: Ablation studies for Reweighting-Induced Improvements on Mistral.

Method	Helpfulness	Honesty	Harmlessness	Norm_Gain
Mistral-7B-Instruct-v0.2	41.70	62.17	76.38	–
Hummer (best mixture)	42.50↑1.92%	62.05↓0.19%	78.57↑2.87%	+1.53%
TSVM (best merging)	43.02↑3.17%	61.10↓1.72%	80.88↑5.89%	+2.45%
RESM w/o Outlier Weighting	42.90↑2.88%	61.80↓0.60%	81.25↑6.38%	+2.89%
RESM w/o Rank Selection	43.32↑3.89%	61.20↓1.56%	81.75↑7.03%	+3.12%
RESM (ours)	43.15↑3.48%	61.50↓1.08%	82.25↑7.69%	**+3.36%**

6 Conclusion

This paper establishes the first benchmark to systematically compare data mixture and model merging methods for balanced optimization across helpfulness, harmlessness, and honesty dimensions to enhance LLMs' alignment. Leveraging this benchmark, we uncover a series of overlooked optimization principles and insights. Specifically, we propose a novel Reweighting-Enhanced Task Singular Merging (RESM) method, which employs outlier weighting and sparsity-aware rank selection strategies to address preference noise accumulation and layer sparsity adaptation challenges during LLM merging for 3H objectives. Our theoretical analyses and experimental results provide a promising pathway for LLM alignment, advancing the development of ethically constrained language models.

ACKNOWLEDGMENTS

This work was supported in part by the National Key Research and Development Program of China (2024YFE0203700), "Pioneer" and "Leading Goose" R&D Program of Zhejiang (2025C02037), and the Starry Night Science Fund of Zhejiang University Shanghai Institute for Advanced Study (SN-ZJU-SIAS-0010). Moreover, this work was also supported by Ant Group Research Intern Program.

References

[1] Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.

[2] An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengen Huang, Chenxu Lv, Chujie Zheng, Dayiheng Liu, Fan Zhou, Fei Huang, Feng Hu, Hao Ge, Haoran Wei, Huan Lin, Jialong Tang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jing Zhou, Jingren Zhou, Junyang Lin, Kai Dang, Keqin Bao, Kexin Yang, Le Yu, Lianghao Deng, Mei Li, Mingfeng Xue, Mingze Li, Pei Zhang, Peng Wang, Qin Zhu, Rui Men, Ruize Gao, Shixuan Liu, Shuang Luo, Tianhao Li, Tianyi Tang, Wenbiao Yin, Xingzhang Ren, Xinyu Wang, Xinyu Zhang, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yinger Zhang, Yu Wan, Yuqiong Liu, Zekun Wang, Zeyu Cui, Zhenru Zhang, Zhipeng Zhou, and Zihan Qiu. Qwen3 technical report, 2025.

[3] ByteDance Seed, Yufeng Yuan, Yu Yue, Mingxuan Wang, Xiaochen Zuo, Jiaze Chen, Lin Yan, Wenyuan Xu, Chi Zhang, Xin Liu, et al. Seed-thinking-v1. 5: Advancing superb reasoning models with reinforcement learning. *arXiv preprint arXiv:2504.13914*, 2025.

[4] Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, et al. Training a helpful and harmless assistant with reinforcement learning from human feedback. *arXiv preprint arXiv:2204.05862*, 2022.

[5] Yiju Guo, Ganqu Cui, Lifan Yuan, Ning Ding, Zexu Sun, Bowen Sun, Huimin Chen, Ruobing Xie, Jie Zhou, Yankai Lin, et al. Controllable preference optimization: Toward controllable multi-objective alignment. *arXiv preprint arXiv:2402.19085*, 2024.

[6] Shashank Sonkar, Kangqi Ni, Sapana Chaudhary, and Richard G Baraniuk. Pedagogical alignment of large language models. *arXiv preprint arXiv:2402.05000*, 2024.

[7] Shu Yang, Jiayuan Su, Han Jiang, Mengdi Li, Keyuan Cheng, Muhammad Asif Ali, Lijie Hu, and Di Wang. Dialectical alignment: Resolving the tension of 3h and security threats of llms. *arXiv preprint arXiv:2404.00486*, 2024.

[8] Yuntao Bai, Saurav Kadavath, Sandipan Kundu, Amanda Askell, Jackson Kernion, Andy Jones, Anna Chen, Anna Goldie, Azalia Mirhoseini, Cameron McKinnon, et al. Constitutional ai: Harmlessness from ai feedback. *arXiv preprint arXiv:2212.08073*, 2022.

[9] Josef Dai, Xuehai Pan, Ruiyang Sun, Jiaming Ji, Xinbo Xu, Mickel Liu, Yizhou Wang, and Yaodong Yang. Safe rlhf: Safe reinforcement learning from human feedback. *arXiv preprint arXiv:2310.12773*, 2023.

[10] Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. *Advances in Neural Information Processing Systems*, 36, 2024.

[11] Jiaming Ji, Donghai Hong, Borong Zhang, Boyuan Chen, Josef Dai, Boren Zheng, Tianyi Qiu, Boxun Li, and Yaodong Yang. Pku-saferlhf: Towards multi-level safety alignment for llms with human preference. *arXiv preprint arXiv:2406.15513*, 2024.

[12] Youcheng Huang, Jingkun Tang, Duanyu Feng, Zheng Zhang, Wenqiang Lei, Jiancheng Lv, and Anthony G Cohn. Dishonesty in helpful and harmless alignment. *arXiv preprint arXiv:2406.01931*, 2024.

[13] Nathan Lambert, Jacob Morrison, Valentina Pyatkin, Shengyi Huang, Hamish Ivison, Faeze Brahman, Lester James V Miranda, Alisa Liu, Nouha Dziri, Shane Lyu, et al. T\" ulu 3: Pushing frontiers in open language model post-training. *arXiv preprint arXiv:2411.15124*, 2024.

[14] Haoxiang Wang, Wei Xiong, Tengyang Xie, Han Zhao, and Tong Zhang. Interpretable preferences via multi-objective reward modeling and mixture-of-experts. *arXiv preprint arXiv:2406.12845*, 2024.

[15] Li Jiang, Yusen Wu, Junwu Xiong, Jingqing Ruan, Yichuan Ding, Qingpei Guo, Zujie Wen, Jun Zhou, and Xiaotie Deng. Hummer: Towards limited competitive preference dataset. *arXiv preprint arXiv:2405.11647*, 2024.

[16] Chuxue Cao, Han Zhu, Jiaming Ji, Qichao Sun, Zhenghao Zhu, Yinyu Wu, Juntao Dai, Yaodong Yang, Sirui Han, and Yike Guo. Safelawbench: Towards safe alignment of large language models. *arXiv preprint arXiv:2506.06636*, 2025.

[17] Alexandre Rame, Guillaume Couairon, Corentin Dancette, Jean-Baptiste Gaya, Mustafa Shukor, Laure Soulier, and Matthieu Cord. Rewarded soups: towards pareto-optimal alignment by interpolating weights fine-tuned on diverse rewards. *Advances in Neural Information Processing Systems*, 36, 2024.

[18] Enneng Yang, Li Shen, Guibing Guo, Xingwei Wang, Xiaochun Cao, Jie Zhang, and Dacheng Tao. Model merging in llms, mllms, and beyond: Methods, theories, applications and opportunities. *arXiv preprint arXiv:2408.07666*, 2024.

[19] Alexandre Ramé, Nino Vieillard, Léonard Hussenot, Robert Dadashi, Geoffrey Cideron, Olivier Bachem, and Johan Ferret. Warm: On the benefits of weight averaged reward models. *arXiv preprint arXiv:2401.12187*, 2024.

[20] Alexandre Ramé, Johan Ferret, Nino Vieillard, Robert Dadashi, Léonard Hussenot, Pierre-Louis Cedoz, Pier Giuseppe Sessa, Sertan Girgin, Arthur Douillard, and Olivier Bachem. Warp: On the benefits of weight averaged rewarded policies. *arXiv preprint arXiv:2406.16768*, 2024.

[21] Yang Gao, Dana Alon, and Donald Metzler. Impact of preference noise on the alignment performance of generative language models. *arXiv preprint arXiv:2404.09824*, 2024.

[22] Guangyuan Shi, Zexin Lu, Xiaoyu Dong, Wenlong Zhang, Xuanyu Zhang, Yujie Feng, and Xiao-Ming Wu. Understanding layer significance in llm alignment. *arXiv preprint arXiv:2410.17875*, 2024.

[23] Shen Li, Liuyi Yao, Lan Zhang, and Yaliang Li. Safety layers in aligned large language models: The key to llm security. *arXiv preprint arXiv:2408.17003*, 2024.

[24] Arash Ahmadian, Seraphina Goldfarb-Tarrant, Beyza Ermis, Marzieh Fadaee, Sara Hooker, et al. Mix data or merge models? optimizing for diverse multi-task learning. *arXiv preprint arXiv:2410.10801*, 2024.

[25] Selim Furkan Tekin, Fatih Ilhan, Tiansheng Huang, Sihao Hu, Zachary Yahn, and Ling Liu. H3 fusion: Helpful, harmless, honest fusion of aligned llms. *arXiv preprint arXiv:2411.17792*, 2024.

[26] Atoosa Chegini, Hamid Kazemi, Seyed Iman Mirzadeh, Dong Yin, Maxwell Horton, Moin Nabi, Mehrdad Farajtabar, and Keivan Alizadeh. Model soup for better rlhf: Weight space averaging to improve alignment in llms. In *NeurIPS 2024 Workshop on Fine-Tuning in Modern Machine Learning: Principles and Scalability*, 2024.

[27] Alexey Gorbatovski, Boris Shaposhnikov, Alexey Malakhov, Nikita Surnachev, Yaroslav Aksenov, Ian Maksimov, Nikita Balagansky, and Daniil Gavrilov. Learn your reference model for real good alignment. *arXiv preprint arXiv:2404.09656*, 2024.

[28] Keming Lu, Bowen Yu, Fei Huang, Yang Fan, Runji Lin, and Chang Zhou. Online merging optimizers for boosting rewards and mitigating tax in alignment. *arXiv preprint arXiv:2405.17931*, 2024.

[29] Fanqi Wan, Xinting Huang, Deng Cai, Xiaojun Quan, Wei Bi, and Shuming Shi. Knowledge fusion of large language models. *arXiv preprint arXiv:2401.10491*, 2024.

[30] Ziyi Yang, Fanqi Wan, Longguang Zhong, Tianyuan Shi, and Xiaojun Quan. Weighted-reward preference optimization for implicit model fusion. *arXiv preprint arXiv:2412.03187*, 2024.

[31] Tzu-Han Lin, Chen-An Li, Hung-yi Lee, and Yun-Nung Chen. Dogerm: Equipping reward models with domain knowledge through model merging. *arXiv preprint arXiv:2407.01470*, 2024.

[32] Megh Thakkar, Yash More, Quentin Fournier, Matthew Riemer, Pin-Yu Chen, Amal Zouaq, Payel Das, and Sarath Chandar. Combining domain and alignment vectors to achieve better knowledge-safety trade-offs in llms. *arXiv preprint arXiv:2411.06824*, 2024.

[33] Hasan Abed Al Kader Hammoud, Umberto Michieli, Fabio Pizzati, Philip Torr, Adel Bibi, Bernard Ghanem, and Mete Ozay. Model merging and safety alignment: One bad model spoils the bunch. *arXiv preprint arXiv:2406.14563*, 2024.

[34] Jinluan Yang, Anke Tang, Didi Zhu, Zhengyu Chen, Li Shen, and Fei Wu. Mitigating the backdoor effect for multi-task model merging via safety-aware subspace. *arXiv preprint arXiv:2410.13910*, 2024.

[35] Yiming Ju, Ziyi Ni, Xingrun Xing, Zhixiong Zeng, Siqi Fan, Zheng Zhang, et al. Mitigating training imbalance in llm fine-tuning via selective parameter merging. *arXiv preprint arXiv:2410.03743*, 2024.

[36] Yong Lin, Lu Tan, Hangyu Lin, Zeming Zheng, Renjie Pi, Jipeng Zhang, Shizhe Diao, Haoxiang Wang, Han Zhao, Yuan Yao, et al. Speciality vs generality: An empirical study on catastrophic forgetting in fine-tuning foundation models. *arXiv preprint arXiv:2309.06256*, 2023.

[37] Yong Lin, Hangyu Lin, Wei Xiong, Shizhe Diao, Jianmeng Liu, Jipeng Zhang, Rui Pan, Haoxiang Wang, Wenbin Hu, Hanning Zhang, et al. Mitigating the alignment tax of rlhf. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 580–606, 2024.

[38] Xin Yi, Shunfan Zheng, Linlin Wang, Xiaoling Wang, and Liang He. A safety realignment framework via subspace-oriented model fusion for large language models. *arXiv preprint arXiv:2405.09055*, 2024.

[39] Joel Jang, Seungone Kim, Bill Yuchen Lin, Yizhong Wang, Jack Hessel, Luke Zettlemoyer, Hannaneh Hajishirzi, Yejin Choi, and Prithviraj Ammanabrolu. Personalized soups: Personalized large language model alignment via post-hoc parameter merging. *arXiv preprint arXiv:2310.11564*, 2023.

[40] Weixiang Zhao, Yulin Hu, Zhuojun Li, Yang Deng, Yanyan Zhao, Bing Qin, and Tat-Seng Chua. Towards comprehensive and efficient post safety alignment of large language models via safety patching. *arXiv preprint arXiv:2405.13820*, 2024.

[41] Yufei Wang, Wanjun Zhong, Liangyou Li, Fei Mi, Xingshan Zeng, Wenyong Huang, Lifeng Shang, Xin Jiang, and Qun Liu. Aligning large language models with human: A survey. *arXiv preprint arXiv:2307.12966*, 2023.

[42] Yang Liu, Yuanshun Yao, Jean-Francois Ton, Xiaoying Zhang, Ruocheng Guo, Hao Cheng, Yegor Klochkov, Muhammad Faaiz Taufiq, and Hang Li. Trustworthy llms: a survey and guideline for evaluating large language models' alignment. *arXiv preprint arXiv:2308.05374*, 2023.

[43] Jiaming Ji, Boyuan Chen, Hantao Lou, Donghai Hong, Borong Zhang, Xuehai Pan, Tianyi Alex Qiu, Juntao Dai, and Yaodong Yang. Aligner: Efficient alignment by learning to correct. *Advances in Neural Information Processing Systems*, 37:90853–90890, 2024.

[44] Federico Bianchi, Mirac Suzgun, Giuseppe Attanasio, Paul Röttger, Dan Jurafsky, Tatsunori Hashimoto, and James Zou. Safety-tuned llamas: Lessons from improving the safety of large language models that follow instructions. *arXiv preprint arXiv:2309.07875*, 2023.

[45] Avinash Amballa, Durga Sandeep Saluru, Gayathri Akkinapalli, Abhishek Sureddy, and Akshay Kumar Sureddy. Safe to serve: Aligning instruction-tuned models for safety and helpfulness. *arXiv preprint arXiv:2412.00074*, 2024.

[46] Ralph Allan Bradley and Milton E Terry. Rank analysis of incomplete block designs: I. the method of paired comparisons. *Biometrika*, 39(3/4):324–345, 1952.

[47] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744, 2022.

[48] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

[49] Zhilin Wang, Yi Dong, Jiaqi Zeng, Virginia Adams, Makesh Narsimhan Sreedhar, Daniel Egert, Olivier Delalleau, Jane Polak Scowcroft, Neel Kant, Aidan Swope, et al. Helpsteer: Multi-attribute helpfulness dataset for steerlm. *arXiv preprint arXiv:2311.09528*, 2023.

[50] Haoxiang Wang, Yong Lin, Wei Xiong, Rui Yang, Shizhe Diao, Shuang Qiu, Han Zhao, and Tong Zhang. Arithmetic control of llms for diverse user preferences: Directional preference alignment with multi-objective rewards. *arXiv preprint arXiv:2402.18571*, 2024.

[51] Jing Yu, Yibo Zhao, Jiapeng Zhu, Wenming Shao, Bo Pang, Zhao Zhang, and Xiang Li. Text detoxification: Data efficiency, semantic preservation and model generalization. *arXiv preprint arXiv:2507.01050*, 2025.

[52] Ganqu Cui, Lifan Yuan, Ning Ding, Guanming Yao, Wei Zhu, Yuan Ni, Guotong Xie, Zhiyuan Liu, and Maosong Sun. Ultrafeedback: Boosting language models with high-quality feedback, 2023.

[53] Zeqiu Wu, Yushi Hu, Weijia Shi, Nouha Dziri, Alane Suhr, Prithviraj Ammanabrolu, Noah A Smith, Mari Ostendorf, and Hannaneh Hajishirzi. Fine-grained human feedback gives better rewards for language model training. *Advances in Neural Information Processing Systems*, 36:59008–59033, 2023.

[54] Gabriel Ilharco, Marco Tulio Ribeiro, Mitchell Wortsman, Suchin Gururangan, Ludwig Schmidt, Hannaneh Hajishirzi, and Ali Farhadi. Editing models with task arithmetic. *arXiv preprint arXiv:2212.04089*, 2022.

[55] Prateek Yadav, Derek Tam, Leshem Choshen, Colin A Raffel, and Mohit Bansal. Ties-merging: Resolving interference when merging models. *Advances in Neural Information Processing Systems*, 36, 2024.

[56] Le Yu, Bowen Yu, Haiyang Yu, Fei Huang, and Yongbin Li. Language models are super mario: Absorbing abilities from homologous models as a free lunch. In *Forty-first International Conference on Machine Learning*, 2024.

[57] MohammadReza Davari and Eugene Belilovsky. Model breadcrumbs: Scaling multi-task model merging with sparse masks. In *European Conference on Computer Vision*, pages 270–287. Springer, 2025.

[58] Pala Tej Deep, Rishabh Bhardwaj, and Soujanya Poria. Della-merging: Reducing interference in model merging through magnitude-based sampling. *arXiv preprint arXiv:2406.11617*, 2024.

[59] Dong-Hwan Jang, Sangdoo Yun, and Dongyoon Han. Model stock: All we need is just a few fine-tuned models. In *European Conference on Computer Vision*, pages 207–223. Springer, 2025.

[60] Antonio Andrea Gargiulo, Donato Crisostomi, Maria Sofia Bucarelli, Simone Scardapane, Fabrizio Silvestri, and Emanuele Rodolà. Task singular vectors: Reducing task interference in model merging. *arXiv preprint arXiv:2412.00081*, 2024.

[61] Daniel Marczak, Simone Magistri, Sebastian Cygert, Bartłomiej Twardowski, Andrew D Bagdanov, and Joost van de Weijer. No task left behind: Isotropic model merging with common and task-specific subspaces. *arXiv preprint arXiv:2502.04959*, 2025.

[62] Chanhyuk Lee, Jiho Choi, Chanryeol Lee, Donggyun Kim, and Seunghoon Hong. Adarank: Adaptive rank pruning for enhanced model merging. *arXiv preprint arXiv:2503.22178*, 2025.

[63] Lujun Li, Peijie Dong, Zhenheng Tang, Xiang Liu, Qiang Wang, Wenhan Luo, Wei Xue, Qifeng Liu, Xiaowen Chu, and Yike Guo. Discovering sparsity allocation for layer-wise pruning of large language models. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024.

[64] Zhenhong Zhou, Haiyang Yu, Xinghua Zhang, Rongwu Xu, Fei Huang, and Yongbin Li. How alignment and jailbreak work: Explain llm safety through intermediate hidden states. *arXiv preprint arXiv:2406.05644*, 2024.

[65] Olivier Roy and Martin Vetterli. The effective rank: A measure of effective dimensionality. In *2007 15th European signal processing conference*, pages 606–610. IEEE, 2007.

[66] Jondurbin. Dataset. `https://huggingface.co/datasets/jondurbin/py-dpo-v0.1`, 2024.

[67] Wing Lian, Bleys Goodson, Eugene Pentland, Austin Cook, Chanvichet Vong, and "Teknium". Openorca: An open dataset of gpt augmented flan reasoning traces. `https://https://huggingface.co/datasets/Open-Orca/OpenOrca`, 2023.

[68] Luigi Daniele and Suphavadeeprasit. Amplify-instruct: Synthetically generated diverse multi-turn conversations for efficient llm training. *arXiv preprint arXiv:(coming soon)*, 2023.

[69] Jondurbin. Dataset. `https://huggingface.co/datasets/jondurbin/truthy-dpo-v0.1`, 2024.

[70] Weixin Chen, Dawn Song, and Bo Li. Grath: gradual self-truthifying for large language models. *arXiv preprint arXiv:2401.12292*, 2024.

[71] Banghua Zhu, Evan Frick, Tianhao Wu, Hanlin Zhu, and Jiantao Jiao. Starling-7b: Improving llm helpfulness and harmlessness with rlaif, November 2023.

[72] Yu Meng, Mengzhou Xia, and Danqi Chen. Simpo: Simple preference optimization with a reference-free reward. *arXiv preprint arXiv:2405.14734*, 2024.

[73] Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

[74] Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. Mistral 7b. *arXiv preprint arXiv:2310.06825*, 2023.

[75] Charles Goddard, Shamane Siriwardhana, Malikeh Ehghaghi, Luke Meyers, Vlad Karpukhin, Brian Benedict, Mark McQuade, and Jacob Solawetz. Arcee's mergekit: A toolkit for merging large language models. *arXiv preprint arXiv:2403.13257*, 2024.

[76] Mitchell Wortsman, Gabriel Ilharco, Samir Ya Gadre, Rebecca Roelofs, Raphael Gontijo-Lopes, Ari S Morcos, Hongseok Namkoong, Ali Farhadi, Yair Carmon, Simon Kornblith, et al. Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time. In *International conference on machine learning*, pages 23965–23998. PMLR, 2022.

[77] Jiawei Liu, Chunqiu Steven Xia, Yuyao Wang, and Lingming Zhang. Is your code generated by chatgpt really correct? rigorous evaluation of large language models for code generation. *Advances in Neural Information Processing Systems*, 36, 2024.

[78] Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. Judging llm-as-a-judge with mt-bench and chatbot arena. *Advances in Neural Information Processing Systems*, 36:46595–46623, 2023.

[79] Zhiying Zhu, Yiming Yang, and Zhiqing Sun. Halueval-wild: Evaluating hallucinations of language models in the wild. *arXiv preprint arXiv:2403.04307*, 2024.

[80] Lijun Li, Bowen Dong, Ruohui Wang, Xuhao Hu, Wangmeng Zuo, Dahua Lin, Yu Qiao, and Jing Shao. Salad-bench: A hierarchical and comprehensive safety benchmark for large language models. *arXiv preprint arXiv:2402.05044*, 2024.

[81] Justin Cui, Wei-Lin Chiang, Ion Stoica, and Cho-Jui Hsieh. Or-bench: An over-refusal benchmark for large language models. *arXiv preprint arXiv:2405.20947*, 2024.

[82] Mingjie Sun, Zhuang Liu, Anna Bair, and J Zico Kolter. A simple and effective pruning approach for large language models. *arXiv preprint arXiv:2306.11695*, 2023.

[83] Lu Yin, You Wu, Zhenyu Zhang, Cheng-Yu Hsieh, Yaqing Wang, Yiling Jia, Gen Li, Ajay Jaiswal, Mykola Pechenizkiy, Yi Liang, et al. Outlier weighed layerwise sparsity (owl): A missing secret sauce for pruning llms to high sparsity. *arXiv preprint arXiv:2310.05175*, 2023.

[84] Wenxiao Wang, Wei Chen, Yicong Luo, Yongliu Long, Zhengkai Lin, Liye Zhang, Binbin Lin, Deng Cai, and Xiaofei He. Model compression and efficient inference for large language models: A survey. *arXiv preprint arXiv:2402.09748*, 2024.

[85] Zixuan Zhou, Xuefei Ning, Ke Hong, Tianyu Fu, Jiaming Xu, Shiyao Li, Yuming Lou, Luning Wang, Zhihang Yuan, Xiuhong Li, et al. A survey on efficient inference for large language models. *arXiv preprint arXiv:2404.14294*, 2024.

[86] Anke Tang, Li Shen, Yong Luo, Shuai Xie, Han Hu, Lefei Zhang, Bo Du, and Dacheng Tao. Smile: Zero-shot sparse mixture of low-rank experts construction from pre-trained foundation models. *arXiv preprint arXiv:2408.10174*, 2024.

[87] Shenghe Zheng and Hongzhi Wang. Free-merging: Fourier transform for model merging with lightweight experts. *arXiv preprint arXiv:2411.16815*, 2024.

[88] Enneng Yang, Zhenyi Wang, Li Shen, Shiwei Liu, Guibing Guo, Xingwei Wang, and Dacheng Tao. Adamerging: Adaptive model merging for multi-task learning. *arXiv preprint arXiv:2310.02575*, 2023.

[89] Amin Heyrani Nobari, Kaveh Alimohammadi, Ali ArjomandBigdeli, Akash Srivastava, Faez Ahmed, and Navid Azizan. Activation-informed merging of large language models. *arXiv preprint arXiv:2502.02421*, 2025.

[90] Shuqi Liu, Han Wu, Bowei He, Xiongwei Han, Mingxuan Yuan, and Linqi Song. Sens-merging: Sensitivity-guided parameter balancing for merging large language models. *arXiv preprint arXiv:2502.12420*, 2025.

[91] Ziyu Zhao, Yixiao Zhou, Zhi Zhang, Didi Zhu, Tao Shen, Zexi Li, Jinluan Yang, Xuwu Wang, Jing Su, Kun Kuang, et al. Each rank could be an expert: Single-ranked mixture of experts lora for multi-task learning. *arXiv preprint arXiv:2501.15103*, 2025.

[92] Zihang Liu, Yuanzhe Hu, Tianyu Pang, Yefan Zhou, Pu Ren, and Yaoqing Yang. Model balancing helps low-data training and fine-tuning. *arXiv preprint arXiv:2410.12178*, 2024.

[93] Yuanzhe Hu, Kinshuk Goel, Vlad Killiakov, and Yaoqing Yang. Eigenspectrum analysis of neural networks without aspect ratio bias. *arXiv preprint arXiv:2506.06280*, 2025.

[94] Olga Kovaleva, Saurabh Kulshreshtha, Anna Rogers, and Anna Rumshisky. Bert busters: Outlier dimensions that disrupt transformers. *arXiv preprint arXiv:2105.06990*, 2021.

[95] Giovanni Puccetti, Anna Rogers, Aleksandr Drozd, and Felice Dell'Orletta. Outliers dimensions that disrupt transformers are driven by frequency. *arXiv preprint arXiv:2205.11380*, 2022.

[96] Pengxiang Li, Lu Yin, Xiaowei Gao, and Shiwei Liu. Owlore: Outlier-weighed layerwise sampled low-rank projection for memory-efficient llm fine-tuning. *arXiv preprint arXiv:2405.18380*, 2024.

[97] Yaowei Zheng, Richong Zhang, Junhao Zhang, Yanhan Ye, Zheyan Luo, Zhangchi Feng, and Yongqiang Ma. Llamafactory: Unified efficient fine-tuning of 100+ language models. *arXiv preprint arXiv:2403.13372*, 2024.

[98] Anke Tang, Li Shen, Yong Luo, Han Hu, Bo Du, and Dacheng Tao. Fusionbench: A comprehensive benchmark of deep model fusion. *arXiv preprint arXiv:2406.03280*, 2024.

[99] Kairong Han, Kun Kuang, Ziyu Zhao, Junjian Ye, and Fei Wu. Causal agent based on large language model. *arXiv preprint arXiv:2408.06849*, 2024.

[100] Kairong Han, Wenshuo Zhao, Ziyu Zhao, JunJian Ye, Lujia Pan, and Kun Kuang. Cat: Causal attention tuning for injecting fine-grained causal knowledge into large language models. *arXiv preprint arXiv:2509.01535*, 2025.

[101] Linxiao Yang, Yunze Tong, Xinyue Gu, and Liang Sun. Explain temporal black-box models via functional decomposition. In *Forty-first International Conference on Machine Learning*.

[102] Xinpeng Dong, Min Zhang, Didi Zhu, Ye Jun Jian, Zhang Keli, Aimin Zhou, Fei Wu, and Kun Kuang. Erict: Enhancing robustness by identifying concept tokens in zero-shot vision language models. In *Forty-second International Conference on Machine Learning*.

[103] Xiangwei Lv, Mengze Li, Jingyuan Chen, Zhiang Dong, Sirui Han, and Beishui Liao. Out-of-distribution detection via llm-guided outlier generation for text-attributed graph. In *Findings of the Association for Computational Linguistics: ACL 2025*, pages 19544–19555, 2025.

[104] Zijing Hu, Fengda Zhang, Long Chen, Kun Kuang, Jiahui Li, Kaifeng Gao, Jun Xiao, Xin Wang, and Wenwu Zhu. Towards better alignment: Training diffusion models with reinforcement learning against sparse rewards. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pages 23604–23614, 2025.

[105] Zijing Hu, Fengda Zhang, and Kun Kuang. D-fusion: Direct preference optimization for aligning diffusion models with visually consistent samples. In *Forty-second International Conference on Machine Learning*, 2025.

[106] Yunze Tong, Fengda Zhang, Didi Zhu, Jun Xiao, and Kun Kuang. Decoding correlation-induced misalignment in the stable diffusion workflow for text-to-image generation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 18187–18196, 2025.

[107] Yunze Tong, Didi Zhu, Zijing Hu, Jinluan Yang, and Ziyu Zhao. Noise projection: Closing the prompt-agnostic gap behind text-to-image misalignment in diffusion models. *arXiv preprint arXiv:2510.14526*, 2025.

NeurIPS Paper Checklist

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification: We clarify our contribution from the benchmark establishment, phenomenon, and principle exploration, and technique contribution in the abstract and introduction.

   Guidelines:

   - The answer NA means that the abstract and introduction do not include the claims made in the paper.
   - The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
   - The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
   - It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: [Yes]

   Justification: We clarify the contribution in the Appendix D.

   Guidelines:

   - The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
   - The authors are encouraged to create a separate "Limitations" section in their paper.
   - The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
   - The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
   - The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
   - The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
   - If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
   - While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. **Theory assumptions and proofs**

   Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

   Answer: [Yes]

Justification: We provide detailed proof in Appendix A.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. **Experimental result reproducibility**

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: We provide the details for experiments in Appendix C.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general. releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
  (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
  (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
  (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
  (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. **Open access to data and code**

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We provide the detailed implementation in Appendix C.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so "No" is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. **Experimental setting/details**

   Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

   Answer: [Yes]

   Justification: We provide the detailed implementation in the experimental part and Appendix C.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
   - The full details can be provided either with the code, in appendix, or as supplemental material.

7. **Experiment statistical significance**

   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

   Answer: [Yes]

   Justification: We provide the detailed implementation in the experimental part and Appendix C.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
   - The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
   - The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
   - The assumptions made should be given (e.g., Normally distributed errors).

- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. **Experiments compute resources**

   Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

   Answer: [Yes]

   Justification: We provide the detailed implementation in Appendix C.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
   - The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
   - The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. **Code of ethics**

   Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics `https://neurips.cc/public/EthicsGuidelines`?

   Answer: [Yes]

   Justification: We provide the detailed implementation in the experimental part and Appendix C.

   Guidelines:

   - The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
   - If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
   - The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. **Broader impacts**

    Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

    Answer: [Yes]

    Justification: We provide the detailed description in the Appendix D.

    Guidelines:

    - The answer NA means that there is no societal impact of the work performed.
    - If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
    - Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

    Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

    Answer: [NA]

    Justification: the paper poses no such risks.

    Guidelines:

    - The answer NA means that the paper poses no such risks.
    - Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
    - Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
    - We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. **Licenses for existing assets**

    Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

    Answer: [NA]

    Justification: The paper does not use existing assets.

    Guidelines:

    - The answer NA means that the paper does not use existing assets.
    - The authors should cite the original paper that produced the code package or dataset.
    - The authors should state which version of the asset is used and, if possible, include a URL.
    - The name of the license (e.g., CC-BY 4.0) should be included for each asset.
    - For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
    - If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
    - For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.

- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

    Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

    Answer: [NA]

    Justification: The paper does not release new assets.

    Guidelines:

    - The answer NA means that the paper does not release new assets.
    - Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
    - The paper should discuss whether and how consent was obtained from people whose asset is used.
    - At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

    Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

    Answer: [NA]

    Guidelines: The paper does not involve crowdsourcing nor research with human subjects.

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
    - According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

    Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

    Answer: [NA]

    Justification: The paper does not involve crowdsourcing nor research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
    - We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
    - For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [NA]

Justification: The core method development in this research does not involve LLMs as any important, original, or non-standard components.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (`https://neurips.cc/Conferences/2025/LLM`) for what should or should not be described.

The appendix is structured into multiple sections, each offering supplementary information and further clarification on topics discussed in the main body of the manuscript.

A More Details for Method

A.1 More Details for Outlier-Aware Weighting

Interpretation of Dual Objectives for outlier weighting The mathematical framework achieves cross-model consensus and intra-model saliency through its hierarchical thresholding mechanism:

(i) **Cross-Model Consensus**: The denominator in Eq. (3) normalizes each model's contribution by the total sparse outlier magnitude across all n models:

$$\sum_{j=1}^{n}\sum_{c=1}^{d_l} \|\textsc{Threshold}(\boldsymbol{\Delta}_{l,c}^{(j)}, \mu_c^{(j)} + 3\sigma_c^{(j)})\|_1 \tag{10}$$

This forces models with greater sparse deviation magnitudes (potential task conflicts) to receive proportionally reduced aggregation weights $\alpha_l^{(i)}$, effectively suppressing outlier-dominated models in the merged output.

(ii) **Intra-Model Saliency**: The 3σ threshold in $\textsc{Threshold}(\boldsymbol{\Delta}_{l,c}^{(i)}, \mu_c^{(i)} + 3\sigma_c^{(i)})$ implements statistical outlier detection within each model's parameter distribution. For Gaussian-distributed $\Delta_{l,c,k}^{(i)}$ (per Central Limit Theorem), this retains only the top 0.3% extreme deviations that likely correspond to:

- Task-specific knowledge carriers ($\Delta > \mu + 3\sigma$)
- Catastrophic interference sources ($\Delta < \mu - 3\sigma$)

The L_1 norm aggregation $\sum_{c=1}^{d_l} \|\cdot\|_1$ then amplifies layers containing concentrated outlier parameters.

Synergistic Effect: The normalization in (i) prevents any single model's outliers from dominating the merger, while the saliency detection in (ii) preserves critical task-specific features within each model. This dual mechanism reduces interference by selectively blending statistically significant parameters across models.

A.2 More Details for Dynamic Rank Selection

Our method provides enhanced guarantees through statistical awareness and adaptive computation.

(i) Conflict Probability Bound Let $p_{\text{conflict}}^{(l)}$ denote the probability of directional conflicts in layer l. Our rank adaptation yields as follows. We can observe that , compared to TSVM's fixed $\frac{1}{\sqrt{d_l}}$, our bound adapts to layer sparsity.

$$\mathbb{E}[p_{\text{conflict}}^{(l)}] \leq \frac{1}{\sqrt{k_l}} \propto \frac{1}{\sqrt{\lfloor d_l(\gamma_0 + \gamma\Omega_l)\rfloor}} \tag{11}$$

(ii)Theorem Proof for Conflict Probability Bound: Let $(u, v) \in \mathbb{R}^{k_l}$ be random unit vectors representing Task A's and Task B's optimization direction after projection. The conflict probability is defined as follows, assisted by similarity, where ϵ is the conflict threshold (usually set as 0.3):

$$P_{\text{conflict}}^{l} = \mathbb{P}(\cos\theta > \epsilon) = \mathbb{P}(\langle u, v\rangle > \epsilon) \tag{12}$$

We can calculate the concentration onthe Hypersphere by Lévy's concentration lemma as follows:

$$\mathbb{P}(|\mathbf{u}^T\mathbf{v}| \geq t) \leq 2e^{-k_l t^2/2} \tag{13}$$

For previous fixed rank: We can bound the expected conflict probability:

$$\mathbb{E}[P_{\text{conflict}}^{l}] = \int_0^1 \mathbb{P}(|\mathbf{u}^T\mathbf{v}| \geq t)dt \tag{14}$$

$$= \int_0^{\epsilon} 2e^{-k_l t^2/2}dt + \int_{\epsilon}^1 2e^{-k_l t^2/2}dt \tag{15}$$

when $t \in (0, \epsilon)$, this term $\leq 2\epsilon$;

when $t \in (\epsilon, 1)$, this term $\leq 2(1-\epsilon)e^{-k_l\epsilon^2/2}$.

when we choose $\epsilon = \frac{1}{\sqrt{k_1}}$, it becomes:

$$\mathbb{E}[p_{\text{conflict}}] \leq \frac{2}{\sqrt{k_1}} + \frac{2}{e^{1/2}\sqrt{k_1}} \leq \frac{2.5}{\sqrt{k_1}}$$

For our adaptation rank, we can substitute the adaptive rank as follows:

$$k_1 = \lfloor d_l(\gamma_0 + \gamma\Omega_l)\rfloor$$

Thus, we can conclude:

$$\mathbb{E}[p_{\text{conflict}}] \leq \frac{2.5}{\sqrt{\lfloor d_l(\gamma_0 + \gamma\Omega_l)\rfloor}}$$

The key insight includes two parts:

- On the one hand, in $\mathbb{R}^{k_1}$, unit task vectors become increasingly orthogonal (evaluated by the dot product $|\mathbf{u}^\top\mathbf{v}|$) as $k_1 \to \infty$
- On the other hand, sparsity adaptation controls this effect

A.3 Order of Orthogonalization and Rank Selection

A critical design in our RESM algorithm lies in the sequential relationship between orthogonalization (Eq. 1-2) and rank selection (Eq. 9). Through theoretical analysis and empirical validation, we establish that **orthogonalization should precede selection** to ensure optimal subspace alignment and information preservation. This ordering stems from three fundamental considerations below:

(i) Global Orthogonality Constraints: The orthogonal projection in Eq. 1 minimizes the Frobenius norm difference $\|U_{l\perp} - U_l\|_F$ under strict orthogonality constraints. Performing this projection

Table 8: Theoretical Comparison between our proposed RESM and TSVM.

Property	TSVM	RESM
Layer adaptivity	$\times$	✓
Sparsity awareness	$\times$	✓
Conflict bound	$O(d^{-1/2})$	$O(d^{-1/2}(\gamma_0 + \gamma\Omega_l)^{-1/2})$
Weight concentration	Uniform	Heavy-tailed
Comp. complexity	$O(d^3)$	$O(kd^2)$

before selection preserves the complete singular vector structure, enabling accurate modeling of cross-task interference patterns. Early selection would discard essential components for constructing the orthogonal basis, particularly when task-specific updates exhibit heterogeneous rank distributions.

(ii) Dynamic Rank Adaptation: Our sparsity-adaptive rank selection (Eq. 9) requires layer-wise sparsity measurement Ω_l, computed from the full parameter deviation matrix $\boldsymbol{\Delta}_l^{(i)}$. Truncating $\boldsymbol{\Delta}_l^{(i)}$ prematurely would bias Ω_l by excluding contributions from low-magnitude parameters, thereby undermining the adaptive rank calculation. As shown in Algorithm 1, orthogonalization (Step 4) utilizes the full-rank SVD decomposition to maintain statistical fidelity.

(iii) Outlier Weighting Integrity: The outlier-aware weighting mechanism (Eq. 6) operates on the complete parameter deviation matrix to identify statistically significant updates. Rank selection prior to outlier detection would risk eliminating subtle yet critical features masked within lower-rank components, particularly in layers with heavy-tailed parameter distributions.

B More Details for Related Work

B.1 Discussion with the Alignment Tax.

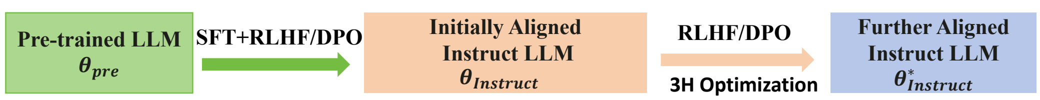


Figure 4: Illustration of Training Stage of 3H Optimization, which aims to further enhance LLMs' alignment from three perspectives based on the existing Initially Aligned LLMs.

We would like to further clarify the main difference between the 3H trade-off and the previously defined alignment tax [37, 28]. In general, the alignment tax describes the phenomenon of RLHF training leading to *the forgetting of pre-trained abilities during the first alignment stage*. However, as shown in Figure 4, we mainly focus on how we can further *enhance the 3H-related abilities of the existing already-aligned model during the second or subsequent stages.* The trade-off mainly comes from the conflict of different alignment objects without dealing with the pre-trained knowledge. Take the Llama3 series for example, alignment tax mainly analyzes the pre-trained ability degradation on the SFT version of the Base LLM (e.g., train the Llama-3-8B on the Ultrachat) while performing DPO training, which refers to the **green arrow** of the Figure 4. However, in this paper, we mainly focus on how can we further enhance the 3H-related abilities of the existing already aligned model (e.g. Llama3-8B-Instruct) during the second or subsequent alignment stages (**orange arrow** of the Figure 4), which can meet more strict demands for specific applications.

B.2 Discussion with the Other Model Merging Methods

To further distinguish our work from previous ones and strengthen our contribution, we provide more detailed discussions about the other model merging methods.

MOE-based merging works need additional input data to train the router: These works, such as SMILES [86], Free-Merging [87], and Twin-Merging [87], aim to balance the performance and deployment costs through modular expertise identification and integration adapted to the input data, which is not designed for 3H optimization in LLM alignment. Recently, we have noticed a concurrent

MOE-fusion work called H3 fusion [25] related to our theme. It includes three main steps:(i) Adopt the instruction tuning and summarization fusion as two modern ensemble learning in the context of helpful-harmless-honest (H3) alignment (ii) **Merge** the aligned model weights with an expert router **according to the type of input** instruction and dynamically select a subset of experts. (iii) Utilize the gating loss and regularization terms to enhance performance. But our work mainly focuses on how we can address the conflict issue for 3H optimization to construct a multi-object aligned LLM rather than dynamically adapting to the input data. Simultaneously, considering that the constraints of data availability and data leak will limit the generalization of existing merging methods for LLMs, in the paper we mainly adopt the well-known and latest **training-free and data-free** merging strategies for dense LLM, while H3 fusion needs the data for training and only utilizes the merging techniques for efficiently adapting to the input data. Thus, **H3 fusion is indeed different from our work from the perspective of problem and technique contributions.**

Other training-based merging works need additional data for test-time adaptation optimization: These works, such as Adamerging [88], AIM-merging[89], Sense-merging[90], Adarank [62], DAM [34], utilize the test-time-adaptation techniques to search for the optimal merging coefficient or prune the rank [91]. Their effectiveness depends heavily on the provided test data. But for 3H optimization, curating high-quality preference data that meets the demand of helpfulness, harmlessness, and honesty simultaneously is difficult due to the complex collective and conflict relationships as stated above. We also need to consider the data mixture problems during test-time adaptation optimization. In this case, we can't compare data mixture and model merging methods for 3H optimization fairly. That's why we only compare the training-free model merging methods in our experimental parts.

B.3 Discussion with the Outlier-Based Sparse LLM Works

To further distinguish our work from previous ones and strengthen our contribution, we provide more detailed discussions about the outlier-based sparse LLM works [92, 93].

Many works investigate the outlier weight in transformer [94, 95] and propose to prune LLM assisted by input activations [82, 83] or sample layer-wise weight during fine-tuning [96]. From the perspective of outlier weight source, the outlier weight updates we addressed are due to the preference noise accumulation while merging different aligned LLMs, which is a special problem for merging for multi-objective alignment. From the perspective of the status of the training process, previous outlier-based sparsity LLM works are only constrained to the parameters of one LLM [84, 85], while we should additionally consider the parameters conflict while merging different LLMs in the process, rather than a post-hoc process on a well-merged LLM. That's why we first perform SVD analysis to separate task-specfic parameters and only adopt outlier-weighting on the singular value.

C More Details for Experiments

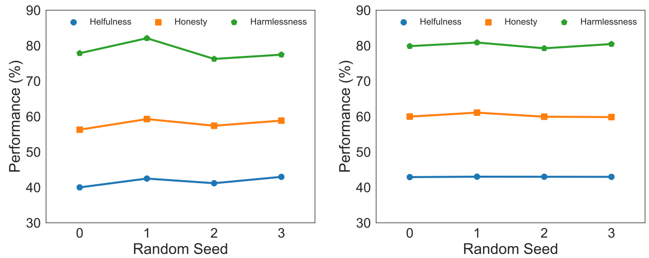
C.1 The Training Details for Model Constructions and Baselines

Training hyperparameters for model constructions: following SimPO [72], based on Llama-3-8B-Instruct and Mistral-7B-Instruct-V2, we conduct preference optimization adopting the fixed batch size 128 for 1 epoch training with the Adam optimizer. We set the max sequence length to 4096 and apply a cosine learning rate schedule with 10 percent warmup steps for each dataset. Specially, we adjust $\beta \in [0.1, 0.5, 1.0, 2.0]$ and learning rate $lr \in [3e-7, 5e-7]$ for model constructions and report the best individual training models corresponding to different annotation dimensions.

The Implementation of Baselines: For Heuristic data mixture methods, we control the ratio between Honesty&Harmlessness and Helpfulness to 1/5,1/10, and 1/20 by default and report the best average score (usually 1/10 according to our experiments). For ArmoRM, we follow the process of SimPO [72] to achieve refined full mixture data. For hummer [15], we refine the alignment dimension conflict (ADC) among preference datasets, leveraging the powerful ability of AI feedback (e.g., GPT4) as the paper stated. For the full mixture datasets of Table 1, we control the ADC lower than 20 percent.

Computation environment: All of our experiments in this paper were conducted on 16×A100 GPUs based on the Llama-Factory [97],MergeKit [75] and fusion bench [98].

Reproducibility: We have made significant efforts to ensure the reproducibility of our work. Upon acceptance, we will release all of the trained models and the complete training and testing code to



(a) DARE-Ties (b) RESM

Figure 5: Comparisons between the random sparsification strategy (e.g.DARE-Ties) and SVD-based strategy (RESM on Mistral under static optimization settings adopting different seeds. RESM can achieve more stable results than random sparsification methods.

facilitate the full reproducibility of our results. We are committed to advancing this work and will provide updates on its accessibility in the future.

C.2 The Evaluation Details for the Judged Models

We provide detailed descriptions for the evaluation that needs the judged models. For MT-Bench, we report scores following its evaluation protocol to grade single answers from 1 to 10 scores assisted by GPT4. For HaluEval-Wild, given prompts to our trained model, we utilize the judged model to check whether the output of our trained model is a hallucination or not and then calculate the no hallucination rate. Similarly, we utilize the prompts from SaladBench and OR-Bench to instruct our trained models and then let the judged models check whether the replies of our trained models are safe/unsafe or refusal/answer. Based on the check results, we can naturally calculate the safe score and refusal score by counting all results. The detailed descriptions of the evaluation can be shown in Table 9. More details can be shown in the original paper.

Table 9: Evaluation details corresponding judge models, scoring types, and metrics.

Evaluation Datasets	**Examples**	**Judge Models**	**Scoring Type**	**Metrics**
MT-Bench [78]	80	GPT-4	Single Answer Grade	Rating of 1-10
HaluEval-Wild [79]	500	GPT4	Classify & Calculate Ratio	Rating of 0-100
SaladBench [80]	1817	MD-Judge-V0.2	Classify & Calculate Ratio	Rating of 0-100
OR-Bench [81]	1319	GPT4-o	Classify & Calculate Ratio	Rating of 0-100

C.3 More Experiments under the Continual DPO Training Settings

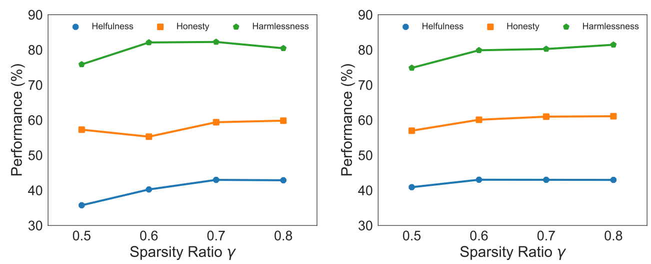
As shown in Table 11, we provide additional results under the continual training settings. Through comparison results between different training stages, we can observe that the honesty, helpfulness,

Table 10: 3H Results on Llama3 Under Continuous Optimization Setting. The normalized gain metric is the average value of relative gain for each dimension compared with the results of Llama3-8B-Instruct.

Methods	**Helpfulness**								**Honesty**	**Harmlessness**		**Helpful_Avg**	**Honest_Avg**	**Harmless_Avg**	**Norm_Gain**
	Math	GSM8K	ARC-E	ARC-C	MMLU	MBPP_Plus	HumanEval_Plus	MT-Bench	HaluEval_Wild	Salad_Bench	OR-Bench				
Llama3-8B-Instruct	28.08	78.09	93.65	82.03	68.20	58.99	53.05	8.25	53.50	91.16	26.97	58.79	53.50	59.07	—
Continual DPO Training Stage1	29.60	77.63	93.47	82.71	68.33	59.79	59.15	8.18	56.00	90.86	39.80	59.86↑1.82%	56.00↑4.67%	65.33↑10.60%	+5.70%
Continual DPO Training Stage2	28.74	74.60	94.00	83.05	68.41	51.59	56.10	8.25	52.20	90.55	77.95	58.09↓1.19%	52.20↓2.43%	84.25↑42.59%	+13.00%
Continual DPO Training Stage3	28.66	76.12	93.05	82.83	68.40	54.57	56.10	8.03	53.20	90.63	71.61	58.72↓0.12%	53.20↓0.56%	81.12↑37.30%	+12.21%
Weight Average	29.78	79.82	93.65	82.37	68.40	58.47	53.65	8.03	53.20	89.58	62.66	59.27↑0.82%	53.20↓0.56%	76.12↑28.83%	+9.70%
Rewarded Soup	29.40	79.76	93.65	82.37	68.48	58.47	54.88	8.15	54.20	89.33	62.75	59.40↑1.04%	54.20↑1.31%	76.04↑28.69%	+10.01%
Model Stock	28.42	79.15	93.65	82.37	68.30	60.05	53.05	8.25	50.60	91.27	28.96	59.16↑0.63%	50.60↓5.42%	60.12↑1.78%	-1.00%
Task Arithmetic	28.72	73.16	92.95	83.05	68.32	52.11	46.34	8.52	51.60	86.07	84.97	56.65↓3.64%	51.60↓3.55%	85.52↑44.74%	+12.52%
Ties	29.18	76.50	93.65	83.39	68.61	56.35	43.78	7.71	52.80	87.55	78.59	57.40↓2.36%	52.80↓1.31%	83.07↑40.60%	+12.31%
DARE	28.18	73.92	92.95	83.05	68.30	51.85	49.39	8.02	52.00	85.76	85.75	56.96↓3.11%	52.00↓2.80%	85.76↑45.15%	+13.08%
DARE Ties	29.48	78.85	93.65	82.37	68.43	59.79	53.66	7.67	52.40	89.46	71.38	59.24↑0.77%	52.40↓2.06%	80.42↑36.11%	+11.61%
DELLA	27.68	71.19	93.12	83.05	68.31	48.15	46.34	8.15	51.80	86.58	87.11	55.75↓5.17%	51.80↓3.18%	86.85↑47.00%	+12.89%
DELLA Ties	28.94	72.18	93.47	82.71	68.41	53.97	47.56	8.21	52.20	87.24	84.38	56.93↓3.16%	52.20↓2.43%	85.81↑45.24%	+13.22%
Breadcrumbs	28.92	78.62	93.47	82.71	68.45	55.82	50.00	8.48	52.40	87.88	72.69	58.31↓0.82%	52.40↓2.06%	80.29↑35.89%	+11.00%
Breadcrumbs Ties	29.79	78.77	93.65	83.73	68.37	57.41	56.10	8.57	53.40	88.26	67.64	59.55↑1.29%	53.40↓0.19%	77.95↑31.96%	+11.02%
TSVM	29.86	78.99	93.65	83.71	68.37	58.51	55.40	8.40	53.80	88.68	75.14	59.61↑1.39%	53.80↑0.56%	81.79↑38.46%	+13.47%
RESM(ours)	29.79	78.77	93.65	83.73	68.37	58.45	56.10	8.57	54.50	89.26	75.34	60.05↑2.14%	54.50↑1.87%	82.49↑39.66%	**+14.56%**

Table 11: 3H Results on Mistral Under Continuous Optimization Setting. The normalized gain metric is the average value of relative gain for each dimension compared with the results of Mistral-7B-Instruct-V2.

Methods	Helpfulness								Honesty	Harmlessness		Helpful_Avg	Honest_Avg	Harmless_Avg	Norm_Gain
	Math	GSM8K	ARC-E	ARC-C	MMLU	MBPP_Plus	HumanEval_Plus	MT-Bench	HaluEval_Wild	Salad_Bench(↑)	OR-Bench(↑)				
Mistral-7B-Instruct-V2	9.54	46.17	82.36	72.88	59.97	26.46	28.66	7.55	62.17	78.07	74.68	41.70	62.17	76.38	—
Continual DPO Training Stage1	8.76	43.14	82.01	74.92	59.78	25.93	27.33	7.59	61.33	78.74	77.23	41.18↓1.25%	61.33↓1.35%	77.99↑2.11%	-0.16%
Continual DPO Training Stage2	9.26	36.16	82.54	75.59	60.38	29.88	33.33	7.86	56.40	82.76	78.54	41.88↑0.43%	56.40↓9.28%	80.65↑5.59%	-1.09%
Continual DPO Training Stage3	9.60	40.49	82.54	77.29		26.25	34.15	7.46	57.40	80.77	83.16	42.29↑1.41%	57.40↓7.67%	81.97↑7.32%	+0.35%
Weight Average	10.04	45.72	82.36	75.25	61.03	26.46	31.71	7.56	59.20	78.02	81.43	42.52↑1.97%	59.20↓4.78%	79.73↑4.38%	+0.52%
Rewarded Soup	9.72	46.02	82.19	75.25	61.03	26.46	32.93	7.61	58.60	77.94	81.34	42.65↑2.28%	58.60↓5.74%	79.64↑4.27%	+0.27%
Model Stock	9.74	47.69	82.36	73.56	59.77	24.87	27.44	7.68	61.00	78.51	76.44	41.64↓0.14%	61.00↓1.88%	77.48↑1.44%	-0.53%
Task Arithmetic	9.76	43.06	82.54	75.93	61.27	25.66	32.93	7.46	57.80	78.32	82.35	42.33↑1.51%	57.80↓7.03%	80.34↑5.18%	-0.11%
Ties	10.48	41.55	84.66	76.27	61.60	26.19	30.49	7.46	53.80	78.99	85.43	42.34↑1.53%	53.80↓13.46%	82.21↑7.64%	-1.43%
DARE	10.40	42.99	85.36	75.93	61.54	24.60	33.54	7.54	56.00	78.81	85.21	42.74↑2.49%	56.00↓9.92%	82.01↑7.37%	-0.02%
DARE Ties	10.28	42.00	85.01	76.27	61.61	27.25	32.32	7.43	53.00	79.17	86.50	42.77↑2.57%	53.00↓14.75%	82.84↑8.46%	-1.24%
DELLA	10.18	43.14	84.83	75.25	61.46	26.46	31.71	7.58	55.25	79.35	86.04	42.58↑2.11%	55.25↓11.13%	82.70↑8.28%	-0.25%
DELLA Ties	10.50	40.18	85.89	77.97	61.37	30.16	30.48	7.30	54.80	79.90	87.49	42.98↑3.07%	54.80↓11.85%	83.70↑9.58%	+0.27%
Breadcrumbs	10.56	42.53	84.83	75.59	64.50	24.60	32.32	7.53	52.40	79.42	84.34	42.81↑2.66%	52.40↓15.71%	81.88↑7.20%	-1.95%
Breadcrumbs Ties	10.54	42.46	84.66	76.95	61.47	26.72	29.88	7.45	53.40	79.80	84.57	42.52↑1.97%	53.40↓14.11%	82.19↑7.61%	-1.51%
TSVM	10.52	41.25	85.28	77.21	61.57	29.22	30.48	7.55	54.95	79.90	87.49	42.89↑2.85%	54.95↓11.61%	83.70↑9.58%	+0.27%
RESM(ours)	10.61	41.26	85.18	77.96	61.60	29.91	31.57	7.65	59.15	79.94	87.69	43.25↑3.72%	59.15↓4.97%	83.82↑9.75%	**+2.83%**



(a) DARE-Ties (b) RESM

Figure 6: Parameter sensitive analysis concerning sparsity factor for model merging methods on Mistral under static optimization settings.

and harmlessness of LLMs are interactively enhanced due to forgetting during continual training. Moreover, model merging methods can achieve comparable results to these continual training methods without the need to consider the optimized status at a specific training stage. In other words, model merging paves a new way for continual DPO training, advocating training multiple models from the same start point and then merging them, rather than continually optimizing the model from the previous optimization.

C.4 Hyper-Parameter Analysis

The sparsity-based strategy is closely related to the merging effect. As shown in Table 3 and Table 4, apart from the SVD-based methods, the most effective merging methods are DARE and DELLA, both of which depend on random sparsification as shown in Table 2. However, we conduct extended studies to check the robustness and stability with respect to random seed and sparsity factors. As shown in Figure 5 and Figure 6, we can observe that RESM can achieve better robust results than previous random sparsification-based methods, further verifying the effectiveness of our methods.

D Broad Impact and Limitation

Our results demonstrate that the main improvement of RESM comes from the honest and harmless aspects. This can reflect the decrease in conflict between them, which can be defined as inter-aspect conflict reduction. But for helpfulness, RESM is still worse than data mixture methods on Llama3, and the improvement on Mistral compared with the existing merging strategy is also minimal. Though the initial goal of honest and harmless training is not designed for helpfulness, modern preference datasets inherently encode helpfulness as a baseline annotation, forcing the alignment process to optimize towards this dimension regardless of their primary target (honesty/harmlessness). This means every alignment vector can represent helpfulness and one or more other dimensions' optimization directions, which may lead to conflict between alignment vectors only from the helpful dimension (e.g. code and commonsense QA abilities for LLM), which can be defined as intra-dimension conflict. This phenomenon necessitates a hierarchical conflict resolution framework to improve model merging for 3H optimization, considering these two categories of conflicts simultaneously. Moreover, deploying model merging methods for other trustworthy concerns [99–103] across more diverse circumstances [104–107, 106] should also be considered.