LoRA on the Go: Instance-level Dynamic LoRA Selection and Merging

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Abstract

Low-Rank Adaptation (LoRA) has emerged as a parameter-efficient approach for fine-tuning large language models. However, conventional LoRA adapters are typically trained for a single task, limiting their applicability in real-world settings, where inputs may span multiple, diverse task domains. At inference time, existing methods can combine multiple LoRAs to improve cross-task performance, but they require additional labeled data or task-specific training, which is expensive at scale.

In this work, we introduce LoRA on the Go (LoGo), a training-free framework that dynamically selects and merges adapters at the instance level without any additional requirements. LoGo leverages signals extracted from a single forward pass through LoRA adapters, to identify the most relevant adapters and determine their contributions on-the-fly. Across 5 NLP benchmarks, 27 datasets, and 3 model families, LoGo outperforms training-based baselines on some tasks upto a margin of 3.6% while remaining competitive on other tasks and maintaining inference throughput, highlighting its effectiveness and practicality.

1 Introduction

Recent advances in large language models (LLMs) such as LLaMA (Dubey et al., 2024) and DeepSeek (Bi et al., 2024) have led to remarkable progress across diverse natural language processing (NLP) tasks. While these models demonstrate strong generalization capabilities, achieving state-of-the-art results in specialized domains often requires task-specific fine-tuning (Wei et al., 2022). However, the massive scale of modern LLMs makes full fine-tuning computationally prohibitive, motivating research on Parameter-Efficient Fine-Tuning (PEFT) methods that adapt models by updating only a small subset of parameters (Houlsby et al., 2019; Li and Liang, 2021; Liu et al., 2022). Among them, Low-Rank Adaptation (LoRA) (Hu et al., 2022) is particularly effective, introducing trainable low-rank matrices while freezing pre-trained weights, thus reducing trainable parameters without sacrificing performance.

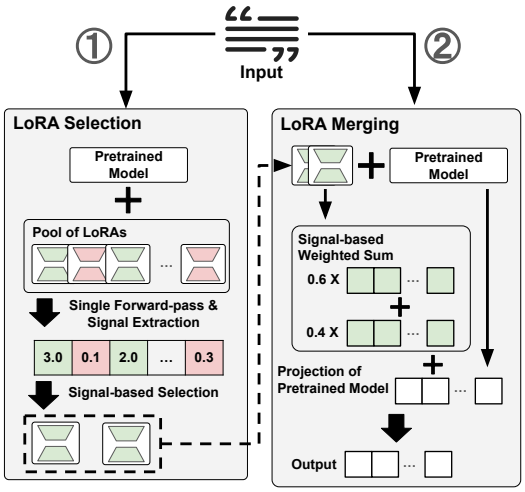


Figure 1: Overall workflow of the proposed LoRA on the Go (LoGo) framework.

Although LoRA provides an efficient adaptation mechanism, the adaptors are typically optimized for a single task domain. In contrast, real-world applications increasingly demand generalization to unseen tasks or tasks that require specialization across multiple task domains. Recent works (Huang et al., 2024; Zhao et al., 2024) explore the possibility of simultaneously leveraging multiple LoRAs trained on diverse tasks.

Existing multi-LoRA approaches share a key limitation: when composing LoRAs together, they need to first select relevant LoRAs from a pool and then they need to merge them. For both steps, they assume well-defined mixed-tasks and rely on labeled data. For instance, LoRAHub (Huang et al., 2024) learns fixed composition weights for each new mixed-task using labeled samples from the target input distribution, while LoRARetriever (Zhao et al., 2024) trains a retrieval model to select relevant LoRAs, but the retrieval model still depends on labeled examples to compute retrieval embeddings.

Such dependence on task homogeneity and labeled supervision restricts scalability in real-world scenarios, where LoRAs may be continually added or updated and labeled data may be unavailable.

In generic conversational systems such as AI copilots (Microsoft, 2023) or multi-domain assistants (OpenAI, 2023; Gemini, 2023), these assumptions rarely hold. User queries are highly heterogeneous, often privacy-sensitive, and may transition across unrelated tasks (e.g., summarization, translation, coding) without explicit task boundaries. Meanwhile, LoRA pools evolve dynamically as new adapters are introduced or deprecated, making task-specific retraining or labeled data collection expensive and impractical. These challenges motivate our central research question: ***How can we dynamically select suitable LoRAs for each input, given an evolving LoRA pool and heterogeneous tasks, without labeled data or retraining?***

In this work, we introduce **Lo**RA on the **Go** (**LoGo**), a framework that operates without any pre-defined data or retraining assumptions, enabling seamless integration with a dynamic LoRA pool. Fig. 1 illustrates the workflow of LoGo. LoGo adopts an **instance-specific** perspective-selecting and merging LoRAs on the fly for each input. Since selection and merging must occur over many candidates in real time, our method is entirely training-free. The core intuition is that *LoRA activations already encode signals of relevance*: when a LoRA is well-suited to an input, its updates exert stronger influence on model outputs (e.g., inference for WNLI (Levesque et al., 2012) benefits from LoRAs trained on SNLI (Bowman et al., 2015) and MNLI (Williams et al., 2018)).

Building on this, LoGo extracts simple yet informative signals—such as the norm or entropy of LoRA activations—from a single forward pass with all LoRAs attached. These signals are used to identify relevant adapters, which are then merged via a weighted sum of activations, where weights are determined by the extracted signals.

We evaluate LoGo on a diverse set of NLP benchmarks spanning 27 datasets, including BIG Bench Hard (BBH) (Suzgun et al., 2023), Translation (Bojar et al., 2014, 2016), Struct-to-Text (Gehrmann et al., 2021; Lin et al., 2020; Nan et al., 2021; Novikova et al., 2017; Gardent et al., 2017), Closed-Book QA (Clark et al., 2018; Kwiatkowski et al., 2019; Joshi et al., 2017), and Natural Language Inference (Nie et al., 2020; Wang et al., 2018). In our experiments, we train LoRAs for three model families over 260 FLANv2 tasks (Wei et al., 2022; Chung et al., 2024).

Results show that LoGo, even without retraining or data assumptions, often surpasses training-based baselines by up to 3.6% on tasks like Struct-to-Test,NLI, while maintaining competitive performance on the rest. LoGo also preserves comparable throughput during selection, merging, and inference. Our analysis confirms that its overhead is amortized in long-output tasks such as summarization or chain-of-thought reasoning, making it highly practical. Across different settings, LoGo shows consistent performance. We will publicly release our code upon acceptance.

Our main contributions are summarized as follows:

- We identify the limitations of existing multiple LoRA-based approaches, which rely on labelled data availability and additional training, making them expensive for real-world deployment.
- We introduce LoRA on the Go (LoGo), a training-free, instance-specific framework that dynamically selects and merges suitable LoRAs for each input using activations extracted in a single forward pass.
- We conduct extensive experiments on 5 standard benchmarks encompassing 27 datasets over 3 model families, showing that LoGo not only outperforms training-based baselines but also has comparable throughput.

2 Related Work

Several studies have explored dynamically combining multiple LoRA adapters, each trained on different tasks, to handle new inputs. Mixture of LoRAs (MoA) trains a router to select a single LoRA (Feng et al., 2024), while LoRAHub merges multiple LoRAs via learning task-specific weights for parameter summation (Huang et al., 2024). Mixture of LoRA Experts (MoLE) similarly learns weights, but applies them to adapter outputs rather than parameters (Wu et al., 2024). All of these methods assume access to labeled samples from the target input distribution and rely on such data to train either the router or the merging weights in a task-specific manner. However, this assumption rarely holds in practice: inputs usually arrive from diverse and unpredictable domains.

LoRARetriever (Zhao et al., 2024) moves toward instance-specific adaptation by retrieving relevant LoRAs using an auxiliary embedding model trained on mixed datasets. However, it requires

training a large embedding model and maintaining dataset samples. Extending this framework to new LoRAs requires (a) samples from the corresponding datasets, and (b) re-computing an embedding point for the new LoRAs in the existing embedding space. This embedding might not be appropriate for out-of-domain (OOD) scenarios, e.g. non-English tasks. Additionally, it may also tamper with the in-domain performance due to entangled embedding points with the OOD LoRAs, Hence, the performance of the resulting model may decline when the inputs deviate significantly from the training distribution of the embedding model.

Recent contemporaneous works have also considered training-free or dynamic LoRA composition. K-LoRA (Ouyang et al., 2025) fuses only two LoRAs with predefined roles, limiting scalability to large adapter pools. Decouple and Orthogonalize (Zheng et al., 2025) is data-free but requires additional optimization and merges all LoRAs without selection. LoRAtorio (Foteinopoulou et al., 2025) computes patch-level similarity for diffusion models, incurring per-step overhead. LoRA-Flow (Wang et al., 2024) trains a router to compute per-token fusion weights, introducing training cost and scalability challenges.

In contrast, LoGo supports instance-specific LoRA selection without training or additional data. By leveraging adapter activations, it identifies relevant LoRAs on the fly, eliminating reliance on auxiliary models or predefined samples.

3 The Proposed LoGo Methodology

The goal of LoGo is to dynamically select and merge the most relevant LoRA adapters for each input, without relying on task-specific training. We begin by formalizing the problem setting, where a pretrained backbone LLM is equipped with a pool of LoRA adapters, each providing low-rank updates to projection matrices (Section 3.1). Given a new input, LoGo performs a single forward pass with all adapters attached, extracts their projection outputs from a designated block, and computes signal scores (e.g., norms or inverse entropy) from these projection outputs to measure adapter relevance. The top-scoring adapters are then selected as candidates (Section 3.2). Next, the selected adapters are merged efficiently through a weighted sum of their outputs, where the weights are directly determined by the extracted signals (Section 3.3). This design allows LoGo to adaptively combine

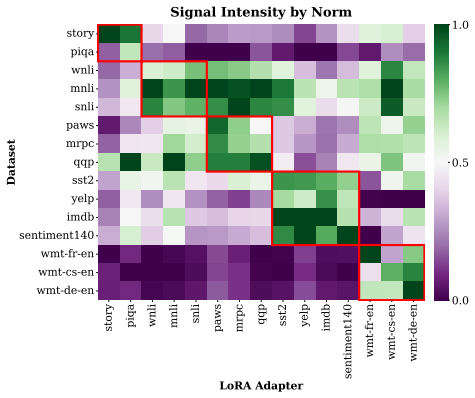


Figure 2: Heatmap illustrating signal patterns across LoRA adapters trained on top of the Qwen-2.5-7B backbone. The x-axis represents LoRAs trained on different tasks, while the y-axis corresponds to datasets from those tasks. Each cell shows the ℓ_2 norm of the projection outputs. The norm values are min-max normalized to [0,1] across datasets for each LoRA. Related task clusters are highlighted in red boxes. More results on signal intensity are in Appendix A.

multiple LoRAs on the fly, while maintaining real-time efficiency and avoiding any additional training overhead. We provide an algorithm that summarizes overall procedure of LoGo in Appendix B.

3.1 Problem Formulation

We consider a setting where a pretrained model f_θ is paired with a set of N LoRA adapters $\mathcal{L} = \{L_i\}_{i=1}^{N}$, each of which is fine-tuned on a distinct task T_i. Given an input sequence $\mathbf{x} = (x_1, ..., x_P)$ of length P, the model generates an output sequence $\mathbf{y} = (y_{P+1}, ..., y_{P+t})$ of length t.

The pretrained model f_θ consists of M Transformer blocks $\mathcal{B} = \{B_j\}_{j=1}^{M}$, where each block B_j contains a self-attention mechanism with head-specific query, key, and value projections, and a feed-forward network. We denote the query and value projection matrices of block B_j (we omit head subscripts for sake of clarity) as $\mathbf{W}_j^{(Q)}$ and $\mathbf{W}_j^{(V)}$, respectively. A LoRA adapter $L_i \in \mathcal{L}$ attaches to the projection matrices $\{(\mathbf{W}_j^{(Q)}, \mathbf{W}_j^{(V)})\}_{j=1}^{M}$ and introduces low-rank updates. For example, for the query projection in block B_j, let $\mathbf{h}_j$ denote the latent input. Then, the adapter L_i produces an update via a low-rank projection $\Delta\mathbf{W}_{i,j}^{(Q)}\mathbf{h}_j$, where $\Delta\mathbf{W}_{i,j}^{(Q)} = \alpha_{i,j}\mathbf{A}_{i,j}\mathbf{B}_{i,j}$. Here, $\mathbf{A}_{i,j}$ and $\mathbf{B}_{i,j}$ are the low-rank matrices of LoRA, and $\alpha_{i,j}$ is a scaling factor.

3.2 Selection of Instance-specific LoRAs

To identify the relevant LoRAs for a given input, LoGo relies on signals extracted during a single

forward pass (probe pass) through the base model f_θ equipped with all available adapters in $\mathcal{L}$. Unlike prior approaches that require additional training, our method is training-free. The procedure incurs only the cost of one token generation, making it practical even under real-time constraints.

Formally, we define the *adapter-augmented model* $f_{\theta,\mathcal{L}}$ as the base model f_θ where every adapter $L_i \in \mathcal{L}$ is attached to its designated projection matrices. Let $B_T \in \mathcal{B}$ denote the target block from which we extract signals, and let $\mathbf{h}_T$ be the hidden representation entering block B_T. For each adapter $L_i \in \mathcal{L}$ attached to query projection matrix $\mathbf{W}_T^{(Q)}$ of B_T, we define projection output as

$$\mathbf{o}_{i,T} = \Delta\mathbf{W}_{i,T}^{(Q)}\mathbf{h}_T, \tag{1}$$

where $\Delta\mathbf{W}_{i,T}^{(Q)} = \alpha_{i,T}\mathbf{A}_{i,T}\mathbf{B}_{i,T}$ is the low-rank update from L_i as defined in Section 3.1. From each projection, we compute a scalar *signal score* s_i that quantifies the relevance of adapter L_i to the given input. Typical examples include the ℓ_2 norm,

$$s_i = \|\mathbf{o}_{i,T}\|_2, \tag{2}$$

or entropy-based measures,

$$p_{i,T}^{(j)} = \frac{\exp(o_{i,T}^{(j)})}{\sum_k \exp(o_{i,T}^{(k)})}, s_i = \left(-\sum_j p_{i,T}^{(j)} \log p_{i,T}^{(j)}\right)^{-1} \tag{3}$$

derived from the projection distribution, both of which capture how strongly a LoRA adapter responds to the input. Intuitively, a larger projection norm indicates stronger activation and thus greater influence on the model's output, while lower-entropy projections imply more confident and focused responses. Hence, these metrics serve as natural indicators of adapter relevance. Here, we take the reciprocal of entropy so that scores are always positive and lower-entropy (i.e., more confident) adapters receive larger weights.

To examine whether these projection-based signals indeed capture task relevance, Fig. 2 demonstrates signal intensities across existing LoRA adapters (from the pool) and datasets. Each column represents a LoRA trained on a specific dataset, while each row represents the dataset used for inference. The heatmap values indicate the normalized signal (here, norm) when each LoRA is applied to samples from different datasets. A clear block-diagonal pattern emerges, highlighted with red boxes, revealing that ***similar tasks activate LoRAs in similar ways***. This observation provides empirical evidence that the extracted signals reflect meaningful semantic relationships among tasks and can effectively guide adapter selection without any additional training.

Finally, based on the collection of signals $\{s_i\}_{i=1}^N$, we select the *top-k adapter set*

$$\mathcal{S} = \mathrm{TopK}\left(\{(L_i, s_i)\}_{i=1}^N, k\right), \tag{4}$$

which contains the k adapters with the highest scores. This set $\mathcal{S}$ serves as the candidate pool for merging in the next stage (Section 3.3).

3.3 Merging LoRAs

After selecting the top-k adapters $\mathcal{S}$ as described in Section 3.2, the next step is to merge them into the base model. Following prior work (Zhao et al., 2024), we consider two types of merging strategies:

- **Output-based Merging (Mixture).** The projection outputs $\{\mathbf{p}_{i,T}\}_{i\in\mathcal{S}}$ are combined directly at the output level. That is, given hidden input $\mathbf{h}_T$, the merged projection is formed as a weighted sum of the selected adapters' projections.
- **Parameter-based Merging (Fusion).** The low-rank parameter updates $\{\Delta\mathbf{W}_{i,T}^{(Q)}\}_{i\in\mathcal{S}}$ are merged into a single fused update, which is then re-attached to the base model.

While both strategies are possible, LoGo adopts *mixture merging* for efficiency. Parameter-based fusion requires explicit recomputation of the merged weight matrices and re-attaching into the model at every step, which introduces significant overhead in deployment scenarios with many adapters. In contrast, output-based merging avoids additional overhead of parameter-level operations, since it directly discards unselected LoRAs during token generation and combines only the projections of the selected ones.

Formally, let s_i be the signal score of adapter $L_i \in \mathcal{S}$ extracted from the probe pass. We normalize these scores into non-negative weights

$$\tilde{w}_i = \frac{s_i}{\sum_{j\in\mathcal{S}} s_j}, \quad i \in \mathcal{S}. \tag{5}$$

The merged projection is then given by

$$\mathbf{o}_{\text{merge}} = \sum_{i\in\mathcal{S}} \tilde{w}_i\, \mathbf{o}_{i,T}. \tag{6}$$

In practice, this weighted summation can be efficiently implemented by adjusting only the scaling factors of the selected adapters, without modifying or reloading their parameters. This design enables LoGo to adaptively merge multiple LoRAs with minimal runtime overhead, while maintaining flexibility to handle diverse inputs on the fly.

4 Experiments

We conduct extensive experiments to evaluate the performance and computational efficiency of LoGo. Section 4.1 outlines the experimental setup,

		LLaMA-3.1-8B						Qwen-2.5-7B						DeepSeek-LLM-7B-Base					
Task	Metric	Base	Adpater-Soup	LoRAHub	LoRA-Retriever	LoGo (Norm)	LoGo (Entropy)	Base	Adapter-Soup	LoRAHub	LoRA-Retriever	LoGo (Norm)	LoGo (Entropy)	Base	Adapter-Soup	LoRAHub	LoRA-Retriever	LoGo (Norm)	LoGo (Entropy)
BBH																			
Boolean Expressions	EM	58.0	72.7	64.5	**76.7**	71.3	**76.7**	76.7	**77.3**	76.7	**77.3**	74.0	74.7	66.0	**68.0**	55.9	66.7	**68.0**	66.0
Causal Judgement	EM	41.4	48.3	**54.0**	**54.0**	48.3	47.1	59.8	59.8	51.5	59.8	**62.1**	59.8	27.6	**49.4**	43.4	48.3	48.3	14.9
Formal Fallacies	EM	25.3	**52.7**	42.7	49.3	52.0	50.0	53.3	55.3	53.2	**56.7**	54.7	53.3	0.7	**48.7**	31.7	**48.7**	**48.7**	0.0
Navigate	EM	45.3	54.7	48.5	**56.7**	50.0	50.0	50.7	50.7	**52.0**	50.7	50.7	50.7	46.0	52.0	51.7	**54.0**	51.3	53.3
Object Counting	EM	35.3	38.0	**39.1**	20.7	27.3	24.0	41.3	**44.0**	35.2	40.7	**44.0**	43.3	46.0	**46.7**	40.9	44.0	44.0	38.7
Sports Understanding	EM	0.0	8.7	**8.9**	0.0	1.3	3.3	22.7	76.7	73.1	76.7	**80.0**	78.7	0.0	0.0	**26.8**	0.0	0.0	0.7
Web-of-lies	EM	2.0	30.7	21.6	**32.0**	14.7	26.7	5.3	49.3	41.6	**54.0**	49.3	51.3	0.0	0.0	**13.9**	0.0	0.0	0.0
Word Sorting	EM	11.3	34.7	16.7	34.0	41.3	**42.0**	0.0	4.7	1.9	**12.7**	12.0	9.3	3.3	6.0	4.4	**7.3**	5.3	1.3
Average		27.3	**42.5**	37.0	40.4	38.3	40.0	38.7	52.2	48.1	**53.6**	53.3	52.6	23.7	**33.8**	33.6	33.6	33.2	21.9
Translation																			
WMT'14 FR->EN	BLEU	27.7	**29.5**	27.1	28.7	28.6	28.6	28.5	**30.4**	6.0	30.3	**30.4**	30.3	26.0	**27.7**	25.4	27.2	27.0	26.5
WMT'14 EN->FR	BLEU	25.3	27.5	25.2	**27.7**	27.2	27.5	27.8	28.6	5.7	**28.8**	28.7	28.7	19.3	22.3	21.3	22.2	**22.5**	22.0
WMT'16 DE->EN	BLEU	29.8	**31.5**	29.8	30.7	31.0	30.9	28.8	**32.0**	9.5	31.7	31.5	31.4	27.2	**29.2**	27.0	28.1	28.6	27.8
WMT'16 EN->DE	BLEU	20.0	21.3	19.4	21.3	21.6	**21.8**	20.0	**20.6**	4.2	**20.6**	**20.6**	**20.6**	12.6	**15.1**	13.9	14.5	15.0	14.3
WMT'16 RO->EN	BLEU	27.9	28.5	23.9	**29.1**	28.1	28.7	25.5	28.9	6.4	**29.1**	28.9	28.9	25.9	**27.6**	19.5	27.1	26.7	26.0
WMT'16 EN->RO	BLEU	16.3	18.0	16.1	18.3	17.7	**18.4**	15.5	**15.8**	1.1	15.5	15.7	15.7	11.0	14.1	12.5	**14.2**	14.1	13.5
Average		24.5	**26.0**	23.6	25.9	25.7	**26.0**	24.4	**26.0**	5.5	**26.0**	25.9	25.9	20.3	**22.7**	19.9	22.2	22.3	21.7
Struct-to-Text																			
CommonGen	Rouge-1	54.8	55.5	46.8	55.5	**56.0**	**56.0**	52.3	54.5	33.7	**54.7**	**54.7**	54.3	0.0	52.0	51.9	50.8	52.5	**53.5**
	Rouge-2	23.6	24.3	20.4	24.9	24.7	**25.0**	21.5	22.9	14.0	**23.1**	**23.1**	22.5	0.0	21.8	20.9	21.5	21.8	**22.7**
	Rouge-L	44.0	44.6	38.1	45.4	45.5	**45.8**	41.6	44.4	27.6	44.7	**44.8**	44.4	0.0	43.3	42.7	42.8	44.0	**44.7**
DART	Rouge-1	63.9	66.3	53.8	63.6	67.6	**68.7**	71.0	73.0	4.9	73.0	73.2	**73.3**	0.5	62.2	61.3	60.4	**66.5**	50.6
	Rouge-2	37.9	39.7	32.2	37.6	40.9	**42.0**	44.2	47.2	1.8	47.1	47.4	**47.5**	0.3	36.8	36.4	35.4	**40.0**	27.9
	Rouge-L	47.9	49.6	40.7	48.1	50.6	**51.4**	53.8	**56.1**	4.5	55.9	**56.1**	56.0	0.4	47.9	47.3	46.8	**49.4**	38.1
E2ENLG	Rouge-1	65.4	67.2	53.6	64.7	**69.0**	**69.0**	70.0	**71.0**	24.8	70.9	**71.0**	**71.0**	0.0	60.6	58.6	57.8	**65.3**	60.7
	Rouge-2	35.8	37.4	30.0	35.6	38.8	**39.0**	41.1	42.4	13.8	42.5	**42.7**	42.6	0.0	32.8	31.9	30.6	**36.2**	32.2
	Rouge-L	44.6	45.8	36.6	45.1	**46.9**	46.8	48.6	49.6	18.6	49.7	**49.8**	49.6	0.0	42.9	42.1	41.6	**44.9**	42.3
WebNLG	Rouge-1	58.4	66.8	64.2	63.7	68.1	**69.0**	72.3	**73.1**	18.3	72.6	72.6	72.6	0.0	63.4	54.4	60.8	**65.7**	55.5
	Rouge-2	35.8	40.5	38.9	38.2	41.8	**42.5**	46.4	**47.7**	10.8	47.1	46.5	46.4	0.0	39.2	33.2	37.8	**40.7**	32.7
	Rouge-L	45.1	51.3	49.5	49.1	52.1	**53.1**	55.8	**57.1**	14.7	56.6	56.3	56.3	0.0	50.9	44.0	48.8	**51.2**	43.7
Average		46.4	49.1	42.1	47.6	50.2	**50.7**	51.6	**53.3**	15.6	53.2	53.2	53.0	0.1	46.2	43.7	44.6	**48.2**	42.0
Closed-Book QA																			
ARC-c	EM	64.7	67.2	64.8	67.9	69.1	**69.9**	85.9	86.8	86.3	**86.9**	86.6	**86.9**	0.0	43.6	**45.1**	**45.1**	33.0	28.2
ARC-e	EM	78.7	79.6	69.4	79.0	**81.3**	81.2	**91.6**	91.4	22.3	**91.6**	**91.6**	**91.6**	0.0	**58.5**	58.0	56.7	43.6	37.2
Natural Questions	EM	5.3	11.0	7.1	**12.6**	11.1	11.7	4.8	11.8	6.8	**12.8**	12.4	12.3	8.7	**10.3**	8.9	10.2	9.0	9.1
Trivia QA	EM	12.7	14.1	12.2	**15.0**	14.6	14.5	6.6	**11.7**	9.1	11.6	10.5	10.8	10.9	11.8	11.4	**12.1**	11.8	11.3
Average		40.4	43.0	38.4	43.6	44.0	**44.3**	47.2	50.4	31.1	**50.7**	50.3	50.4	4.9	**31.1**	30.8	31.0	24.4	21.4
Natural Language Inference (NLI)																			
ANLI-R1	EM	35.0	39.9	35.2	38.4	42.0	**42.5**	55.5	**61.5**	58.6	61.2	61.3	**61.5**	7.5	33.4	12.8	33.5	**33.6**	33.2
ANLI-R2	EM	32.6	39.4	31.4	40.5	42.4	**42.8**	45.9	53.1	48.9	53.3	53.2	**53.7**	8.6	33.4	30.2	**33.6**	33.4	33.1
ANLI-R3	EM	37.3	40.8	23.1	41.9	43.0	**43.4**	51.2	**54.5**	52.4	54.2	54.3	54.2	4.0	**33.5**	16.3	33.4	**33.5**	33.2
QNLI	EM	31.0	31.0	**41.2**	7.5	16.3	19.9	85.8	**86.2**	46.2	86.1	86.1	86.0	0.2	3.4	**4.3**	2.4	1.4	4.0
Average		34.0	**37.8**	32.7	32.1	35.9	37.2	59.6	**63.8**	51.5	63.7	63.7	**63.8**	5.1	**25.9**	15.9	25.7	25.5	**25.9**

Table 1: Performance of LoGo (with norm- and entropy-based signals) compared to baselines across diverse tasks on the LLaMA-3.1-8B, Qwen-2.5-7B, and DeepSeek-LLM-7B-Base backbones. The best results are in **bold**, the second-best are underlined, and our results are highlighted with a blue background. For Struct-to-Text tasks, the reported average is computed over all ROUGE metrics (Rouge-1, Rouge-2, and Rouge-L).

	Base	Adapter-Soup	Lora-Hub	LoRA-Retriever	LoGo (Norm)	LoGo (Entropy)
Code Refinement	13.8	41.3	33.5	29.2	**46.3**	41.5
Code Translation: Java to C#	0.2	9.1	9.7	10.7	**11.2**	10.6
Code Translation: C# to Java	1.6	9.2	10.4	9.4	7.6	**11.7**
Code-to-Text: Java	**1.8**	1.1	1.5	1.2	1.0	1.1
Code-to-Text: Python	1.5	1.7	3.2	1.5	**6.1**	3.7
Average	3.8	12.5	11.6	10.4	**14.4**	13.7

Table 2: Comparison of LoGo with baselines on unseen mixed-dataset scenarios using the LLaMA-3.1-8B backbone, evaluated on the CodeXGLUE dataset. The best results are in **bold**, the second-best are underlined, and our results are highlighted with a blue background.

including the base models, datasets, and baselines. Section 4.2 reports the performance of LoGo across diverse datasets and in mixed-dataset scenarios, followed by Section 4.3, which analyzes the inference-time throughput of our method.

4.1 Evaluation Setup

Base Models and LoRA Adapters. We use **LLaMA-3.1-8B**, **Qwen-2.5-7B**, and **DeepSeek-LLM-7B-Base** as the base pretrained models in our evaluation. For each model, we train **260 LoRA adapters** on distinct Flan-v2 tasks (Wei et al., 2022; Chung et al., 2024), and then evaluate LoGo as well as other baseline methods using the corresponding pretrained model with these adapters. More details on LoRA training are in Appendix C.1. **We plan to publicly release the adapters trained on all pretrained models.**

Datasets. We evaluate LoGo on a diverse set of benchmarks spanning multiple task categories. For **BIG-Bench Hard (BBH)** (Suzgun et al., 2023), we include Boolean Expressions, Causal Judgement, Formal Fallacies, Navigate, Object Counting, Sports Understanding, Web of Lies, and Word Sorting. For **Machine Translation**, we use datasets from the WMT benchmarks (Bojar et al., 2014, 2016), including WMT'14 FR→EN, WMT'14 EN→FR, WMT'16 DE→EN, WMT'16 EN→DE, WMT'16 RO→EN, and WMT'16 EN→RO. For **Struct-to-Text Generation**, we adopt datasets from the GEM benchmark (Gehrmann et al., 2021), including CommonGen (Lin et al., 2020), DART (Nan et al., 2021), E2ENLG (Novikova et al., 2017), and WebNLG (Gardent et al., 2017). For **Closed Book Question Answering**, we use ARC-c, ARC-e (Clark et al., 2018), Natural Questions (Kwiatkowski et al., 2019), and TriviaQA (Joshi et al., 2017). Finally, for **Natural Lan-**

guage Inference, we evaluate on ANLI-R1, ANLI-R2, ANLI-R3 (Nie et al., 2020), and QNLI (Wang et al., 2018). This collection covers reasoning, translation, structured generation, question answering, and inference tasks, providing a comprehensive evaluation of LoGo under diverse conditions.

Baselines. We compare LoGo against four baselines: **Base**, the base pretrained model without any LoRA adapters; **AdapterSoup** (Chronopoulou et al., 2023), which selects relevant LoRA adapters based on Sentence-BERT similarity between the input and the LoRA training datasets, and merges them via uniform averaging, **LoRAHub** (Huang et al., 2024), which learns weights to merge the parameters of LoRA adapters via weighted summation; and **LoRARetriever** (Zhao et al., 2024), which trains an auxiliary language model to retrieve the most relevant adapters for a given input based on embedding similarity. For LoRARetriever, we report results with *mixture* merging. We use the implementation of all baseline methods following their guidelines.

Implementation Details. For all baselines, we fix the number of selected and merged LoRA adapters to 20 as a balanced and computationally efficient default that provides sufficient coverage of heterogeneous adapter pools, while keeping all other hyperparameters consistent with the default settings of the respective pretrained models.

We use the last Transformer block of each model as the target block for signal extraction, denoted as B_T, as instruction-tuned LoRAs primarily modify high-level behavioral representations in upper layers. Similarly, the signal is extracted from the last token of each input sequence, whose hidden state directly precedes the model's predicted response and is thus most informative for capturing adapter-induced behavior shifts. Ablation studies on the number of selected adapters, the choice of Transformer block, the token used for signal extraction, and the merging method are presented in Appendix D.1, which show that LoGo maintains stable performance across these configurations.

4.2 Evaluation Results

Main Results Table 1 reports the performance of LoGo with norm- and entropy-based signals compared to baseline methods on LLaMA-3.1-8B, Qwen-2.5-7B, and DeepSeek-LLM-7B-Base across multiple datasets. LoGo consistently outperforms the baselines in many tasks and remains competitive in the rest. This outcome is remarkable given that LoGo requires no additional training, whereas the baseline methods rely on fine-tuning.

	Training	Inference					
	LoRA-Hub	Base	Adapter-Soup	LoRA-Hub	LoRA-Retriever	LoGo (Norm)	LoGo (Entropy)
Boolean Expressions	24.52	0.37	2.27	1.76	1.83	2.87	1.73
Causal Judgement	47.59	0.32	0.99	0.36	1.91	1.98	2.07
Formal Fallacies	25.29	0.44	0.67	0.39	1.85	1.77	1.65
Navigate	21.87	0.40	1.71	0.92	1.89	1.86	1.97
Object Counting	23.63	0.41	4.78	1.57	2.06	2.36	1.75
Sports Understanding	16.20	0.72	1.24	0.73	1.99	1.86	1.67
Web-of-lies	17.61	0.38	1.91	1.85	2.38	1.62	1.93
Word Sorting	17.51	0.76	0.83	1.61	2.29	2.32	2.22
Average	24.28	0.47	1.80	1.15	2.03	2.08	1.87

Table 3: Per-sample inference time (in seconds) of LoGo compared with baseline methods for LLaMA-3.1-8B model. For LoRAHub, we additionally report training time for learning task-specific merging weights.

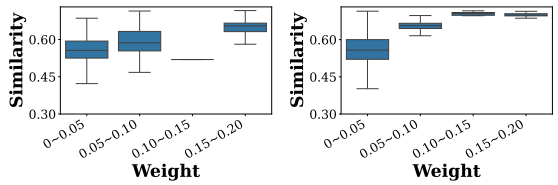
Mixed-dataset Scenario To further assess the generalization ability of LoGo beyond the training domains of the LoRA adapters, we evaluate it on **CodeXGLUE** (Lu et al., 2021), a benchmark comprising diverse programming-language tasks unseen during adapter training. Specifically, we consider five subtasks: Code Refinement, Code Translation (Java→C#), Code Translation (C#→Java), Code-to-Text (Java), and Code-to-Text (Python). All tasks are evaluated using the BLEU metric.

As shown in Table 2, LoGo outperforms all baselines on average. These results indicate that the signal-based selection and merging mechanism in LoGo generalizes effectively to unseen domains, capturing cross-task relevance even when input distributions differ substantially from those of the adapters' training data.

4.3 Computation Time

We also analyze the computational cost of LoGo relative to baseline methods. Table 3 reports per-sample inference times on the LLaMA-3.1-8B model using a single NVIDIA H100 GPU. As expected, the base pretrained model is the fastest, since no adapters are attached. LoRAHub introduces additional overhead and requires training to learn task-specific merging weights (24.28 seconds on average), which limits its practicality when new adapters are frequently introduced.

LoGo, AdapterSoup, and LoRARetriever exhibit comparable inference times (∼2 sec/sample), reflecting the cost of adapter-level operations. Given that AdapterSoup and LoRARetriever require maintaining task datasets, and that LoRARetriever further involves training an auxiliary embedding model, these results underscore the



(a) Norm (b) Entropy

Figure 3: Alignment between merging weights and task similarity of LoGo with (a) norm and (b) entropy as signals for Big-Bench Hard task and Qwen2.5-32B model.

practicality of LoGo.

5 Analysis

We conduct a series of analyses to gain deeper insights into the behavior and design choices of LoGo. Section 5.1 examines the alignment between merging weights and task similarity. Section 5.2 analyzes the characteristics of selected LoRAs. Section 5.4 evaluates the memory consumption and latency introduced by the probe pass in our method. Section D.3 highlights the benefits of LoGo in long-generation scenarios.

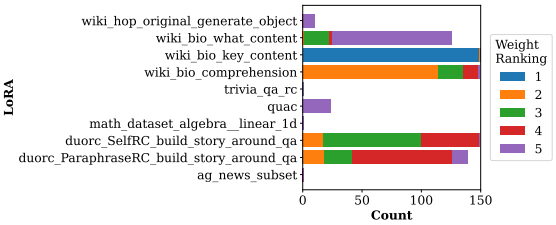
5.1 Alignment with Task Similarity

We examine whether the merging weights produced by LoGo align with task similarity. Since weights in LoGo are derived from projection-based signals, LoRAs trained on similar tasks should assign higher weights to each other's inputs.

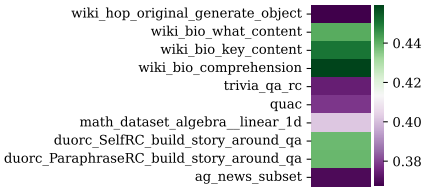
Task similarity is measured as the average cosine similarity, computed from the pretrained model's embeddings between the given input and samples from the FLAN-v2 dataset. Fig. 3 shows a box plot with merging weight on the x-axis and task similarity on the y-axis. The results display a clear upward trend: LoRAs given larger weights correspond to more similar tasks. An exception occurs in the norm-based setting in the weight bucket 0.10–0.15, which appears anomalous because it arises from a single instance out of 22,740 cases (1137 samples $\times$ 20 selected LoRAs). This isolated case manifests as an outlier in the distribution. This confirms that LoGo's signal-based weighting not only enables efficient merging but also captures semantic relations between tasks without additional training.

5.2 Analysis of Selected LoRAs

In this section, we analyze the LoRA adapters selected by LoGo. We employ LoGo with the LLaMA-3.1-8B model on the BBH Word Sorting task and report the selection counts of LoRA



(a) LoRA Selection Count



(b) Task Similarity

Figure 4: Comparison of (a) LoRA selection count by LoGo with Llama-3.1-8B model and (b) task similarity for BBH Word Sorting dataset. Each color in the bar present the priority of the LoRA when it was selected.

	Sample A	Sample B
Question	Sort the following words alphabetically: List: thunderclap swab built poland	Sort the following words alphabetically: List: sanhedrin scratchy helical beau venezuela awash bessie extricable indoeuropean vice pendulum cream animism
Answer	built poland swab thunderclap	animism awash beau bessie cream extricable helical indoeuropean pendulum sanhedrin scratchy venezuela vice

(a) Samples from BBH Word Sorting

	Sample A	Sample B
Question	Given a meaning representation, write a short and simple sentence that contains all the information in the meaning representation. Meaning Representation: [eatType[pub], food[Fast food], customer rating[high], area[riverside], familyFriendly[no], near[Café Rouge]]	Given a meaning representation, write a short and simple sentence that contains all the information in the meaning representation. Meaning Representation: [name[Blue Spice], eatType[pub], food[Chinese], area[city centre], near[Rainbow Vegetarian Café]]
Answer	The Mills is not kid friendly as it is a riverside pub near Café Rouge. Its mid priced fast food is highly rated.	Blue Spice, located near Rainbow Vegetarian Café in the city centre, is a pub that also sells Chinese food. Children should not visit.

(b) Samples from E2ENLG

Dataset	Common	Only in A	Only in B
BBH Word Sorting	wiki_bio_key_content, wiki_bio_what_content	ag_news_subset, math_dataset_algebra __linear_1d, trivia_qa_rc	duorc_SelfRC_build_ story_around_qa, wiki_bio_comprehension, wiki_hop_original_ generate_object
E2ENLG	duorc_ParaphraseRC_ build_story_around_qa, duorc_SelfRC_build_ story_around_qa, wiki_bio_comprehension, wiki_bio_key_content, wiki_bio_what_content	N/A	N/A

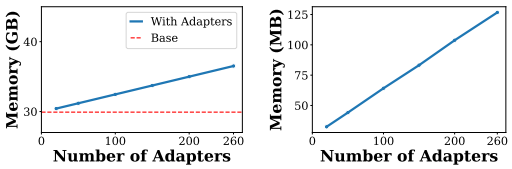
(c) LoRA adapters selected by LoGo

Table 4: Comparison of top-5 selected LoRA adapters for two samples from the BBH Word Sorting and E2ENLG dataset. For the E2ENLG dataset, selected LoRA adapters are common across both samples.

adapters in Figure 4a. Each color within a bar represents the ranking of a LoRA adapter when it was selected. Results show that certain LoRA adapters are consistently selected across samples, although their relative priorities vary considerably. We fur-

Task	Metric	Base	Top1-Adapter	Uniform Weight	Similarity-based	LoGo
BBH	EM	27.3	43.3	33.9	**43.7**	38.3
Translation	BLEU	24.5	23.3	25.1	**25.7**	**25.7**
Struct-to-Text	Rouge	46.4	40.7	48.4	48.9	**50.2**
Closed-Book QA	EM	40.4	40.2	42.6	43.7	**44.0**
NLI	EM	34.0	35.8	33.0	**38.4**	35.9

Table 5: Comparison between LoGo and its variants.



(a) Model Parameters (b) Activation in Probe Pass

Figure 5: Memory usage of LoGo for (a) model parameters and (b) activations during the probe pass.

ther compare these selection frequencies with each adapter's task similarity to the BBH Word Sorting dataset, as shown in Figure 4b. This confirms that LoRAs trained on tasks more similar to the target dataset tend to be selected more frequently.

Anecdotal Examples: We compare the LoRA selections of LoGo for two samples from the BBH Word Sorting and E2ENLG dataset in Table 4. For BBH Word Sorting, a small set of general-purpose adapters (e.g., wiki_bio family) are consistently activated across both samples. These modules are typically associated with reasoning and factual comprehension, providing a general foundation across tasks. Beyond these common adapters, Sample A relies on adapters related to summarization (e.g., ag_news), which facilitate short and structured outputs. In contrast, Sample B engages modules emphasizing long story generation ability (e.g., duorc family). Meanwhile, E2ENLG commonly selects general-purpose comprehension modules, as its story-generation task involves casual content that does not require domain-specific expertise.

5.3 Ablation Study

We conduct an ablation study to evaluate adapter selection and merging strategies. We compare LoGo with its three variants: (1) top-1 adapter selection, (2) merging adapters with uniform weights, and (3) similarity-based adapter selection and merging. All experiments use LLaMA-3.1-8B as backbone, with LoGo using the norm-based weighting. Except for Base and Top-1, all methods select and merge 20 LoRAs.

Table 5 shows that merging multiple adapters consistently outperforms top-1 selection, highlighting the advantage of combining diverse adaptations. Uniform-weight merging is consistently weaker than LoGo's signal-weighted merging, indicating that the weighting mechanism contributes meaningfully to performance. Compared to similarity-based selection, LoGo achieves competitive or better results across task categories while avoiding the need to maintain per-task datasets.

5.4 Scalability Analysis

In this section, we analyze the computational and memory costs of our probe pass based selection procedure with respect to the total adapter pool size N. Note that after selection, LoGo reduces the set to the top-k adapters, where $k \ll N$. All subsequent merging and inference therefore incur the same cost as using only k adapters concurrently.

Memory. The overall additional memory overhead consists of two components: model parameters and activations during the probe pass. Both parameter memory and activation memory scale linearly with the number of adapters (i.e., $O(N)$), as shown in Fig. 5. With LLaMA-3.1-8B and 260 LoRA adapters, the total parameter memory was 6.8 GB, which is $\sim$22% of the pretrained model size (30.6 GB). During the probe pass, we store only a single forward activation per probed layer; hence, the activation overhead is 126.7 MB (i.e., less than 1% of the pretrained model size) even with 260 adapters. We disable KV caching during probing to avoid unnecessary memory usage.

Latency. The probe pass incurs a fixed overhead of $\sim$0.005s per adapter, roughly 8.3% of the forward-pass time without an adapter ($\sim$0.06s).

6 Conclusion

We present LoRA on the Go (LoGo), a training-free framework that dynamically selects and merges LoRA adapters in deployment scenarios without any task-specific training. By extracting lightweight relevance signals from a single forward pass, LoGo identifies the most suitable adapters for each input and merges them through signal-weighted summation. Experiments across diverse NLP benchmarks show that LoGo achieves comparable or better performance than training-based baselines, while maintaining inference throughput. These results highlight the potential of training-free, instance-specific adaptation as a promising direction for deploying large language models in real-world, heterogeneous environments.

Limitations

While LoGo demonstrates strong performance without any task-specific training, several limitations remain. First, our approach relies on projection-based signals extracted from a single forward pass. Although effective in practice, this mechanism does not guarantee that the selected adapters always align with task relevance, particularly in highly out-of-distribution scenarios.

Second, while the probe-based signals implicitly integrate multiple dimensions of relevance through forward activations, they do not explicitly disentangle factors such as topic, style, or skill. Exploring richer signals (e.g., multi-layer probes or attention-based signals) for finer-grained relevance decomposition is an interesting direction for future work.

Third, our experiments primarily use adapters fine-tuned on the FLAN-v2 dataset. Extending evaluation to LoRAs trained on diverse domains (e.g., multimodal, or low-resource data) would help assess generality.

Fourth, the current framework assumes access to a shared pretrained model and a large pool of LoRA adapters. Attaching many adapters simultaneously can increase memory usage and slow inference, making optimization of adapter management (e.g., pruning or selective loading) an important direction for future work.

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Overview of Appendix Sections

- Appendix A: Signals from LoRA Projections
- Appendix B: The LoGo Algorithm
- Appendix C: Additional Details on Experiments
- Appendix D: Additional Results

A Signals from LoRA Projections

We analyze the signal intensity of LoRA projections across datasets for the LLaMA-3.1-8B and Qwen-2.5-7B models, using both norm and entropy as metrics. Fig. 6 presents a heatmap where columns correspond to LoRAs trained on different tasks and rows correspond to datasets from those tasks. Clear block structures emerge, with related tasks highlighted by red boxes, suggesting that similar tasks activate LoRAs in similar ways.

B The LoGo Algorithm

Algorithm 1 summarizes the overall procedure of LoGo.

Algorithm 1 LoGo: Dynamic Selection and Merging of LoRA Adapters

Input: Hidden input $\mathbf{h}_T$ at target block B_T, N tasks LoRAs $\mathcal{L} = \{L_i\}_{i=1}^{N}$, the respective low rank Q-projection update $\Delta W_{i,T}^{(Q)}$, top-k parameter k, scoring method
Output: Merged adapter projection $\mathbf{o}_{\text{merge}}$
Probe pass: Compute each LoRA's projection output
for $i \leftarrow 1 \dots N$ **do**
  $\mathbf{o}_{i,T} \leftarrow \Delta \mathbf{W}_{i,T}^{(Q)} \mathbf{h}_T$
  if scoring method = ℓ_2 **then**
    $s_i \leftarrow \|\mathbf{o}_{i,T}\|_2$
  else if scoring method = entropy **then**
    $p \leftarrow \text{softmax}(\mathbf{o}_{i,T})$
    $s_i \leftarrow 1/\Big(-\sum_j p_j \log p_j\Big)$
  end if
end for
Adapter selection:
$\mathcal{S} \leftarrow \text{TopK}(\{(L_i, s_i)\}, k)$
Normalize weights $\tilde{w}_i = s_i / \sum_{j \in \mathcal{S}} s_j$ for each $L_i \in \mathcal{S}$
Output-based merging:
$\mathbf{o}_{\text{merge}} \leftarrow \sum_{i \in \mathcal{S}} \tilde{w}_i \mathbf{o}_{i,T}$
return $\mathbf{o}_{\text{merge}}$

C Additional Details on Experiments

C.1 Details on LoRA Training

We split each Flan-v2 dataset into training, validation, and test sets with an 8:1:1 ratio. We trained the LoRA adapter with a per-device batch size of 4 and gradient accumulation of 16, resulting in an effective batch size of 64. The learning rate was set to 2×10^{-4}, and training was conducted for 20 epochs. The best model checkpoint was selected based on validation loss. A full list of the Flan-v2 datasets used for training is provided in Table 6.

C.2 Implementation Details

We implement LoGo based on Pytorch (Paszke et al., 2019), Huggingface (Wolf et al., 2020), and PeFT library (Mangrulkar et al., 2022). Specifically we utilize *PeftMixedModel* class, which allows multiple adapters simultaneously and control their scales. We fix the number of selected and merged LoRA adapters to 20, while keeping all other hyperparameters consistent with the default settings of the respective pretrained models used in our experiments. We use the last Transformer block of each model as the target block for signal extraction. Similarly, the signal is extracted from the last token of each input sequence. Since the LoRA adapters are fixed and their respective signals (norm and entropy) are deterministic, we conduct our experiment over a single run.

C.3 Details on Evaluation Datasets

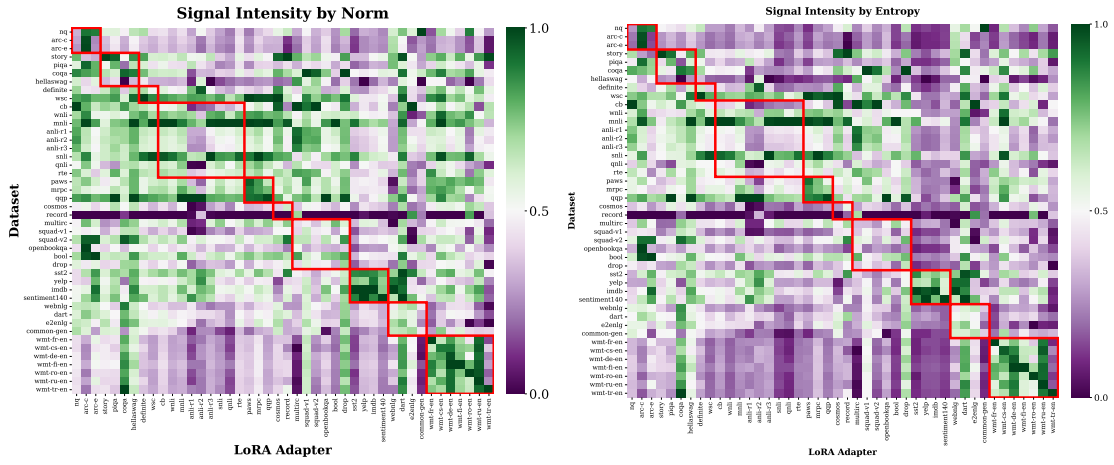
In our evaluation, we used the designated test split of each dataset. When test labels were not available, we relied on the validation or development split for evaluation. For training LoRAHub, we sampled five instances from the training split. For the BIG-Bench Hard datasets, we followed the same train–test split configuration as LoRAHub.

D Additional Results

D.1 Additional Ablation Studies

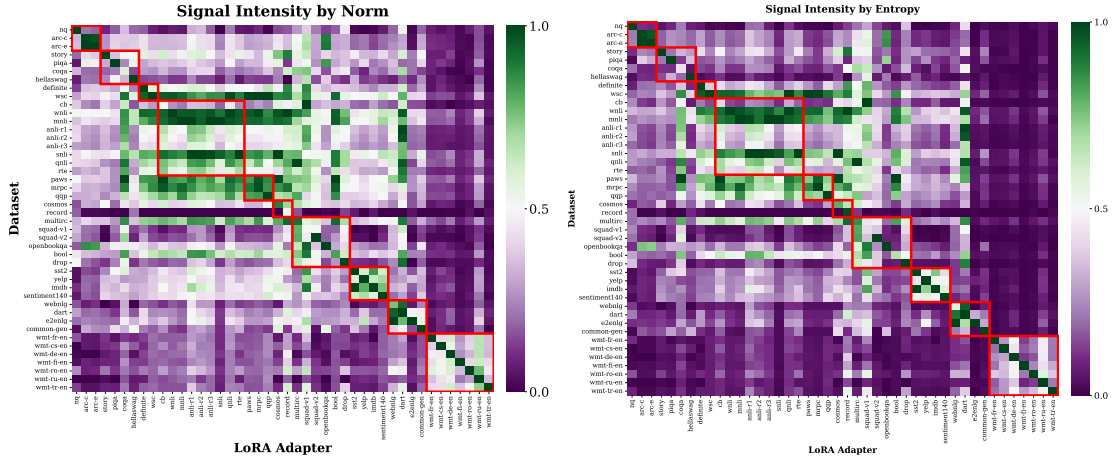
In this section, we conduct ablation studies on LoGo to examine the effects of the token used for signal extraction, the number of selected modules, the specific block used for signal extraction, and merging method. All experiments are performed using LoGo with LLaMA-3.1-8B on the BIG-Bench Hard, Translation, Struct-to-Text, Closed-Book QA, and Natural Language Inference tasks. Evaluation metrics are BLEU for translation, ROUGE for Struct-to-Text, and Exact Match for the other datasets. The reported results are averaged over each dataset category.

Token for Signal Extraction In LoGo, signals are extracted from the projection outputs corresponding to the last token of the input, which serves as our default setting. To investigate the effect



(a) LLaMA-3.1-8B signal intensity by norm

(b) LLaMA-3.1-8B signal Intensity by entropy



(c) Qwen-2.5-7B signal intensity by norm

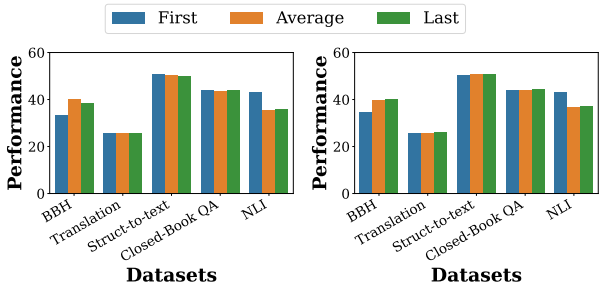
(d) Qwen-2.5-7B signal Intensity by entropy

Figure 6: Heatmaps illustrating signal intensity patterns across LoRA adapters trained on top of the LLaMA-3.1-8B and Qwen-2.5-7B backbone. The x-axis represents LoRAs trained on different tasks, while the y-axis corresponds to datasets from those tasks. Each cell shows the norm or (1 / entropy) of the projection outputs. The cell values are min-max normalized across datasets for each LoRA. The related tasks are highlighted in red boxes.

Category	Datasets (Flan-v2 subsets used)
Question Answering	adversarial_qa_dbert_*, adversarial_qa_dbidaf_*, adversarial_qa_droberta_*, ai2_arc_ARC-Challenge, ai2_arc_ARC-Easy, bool_q, coqa, cosmos_qa, drop, duorc_ParaphraseRC_*, duorc_SelfRC_*, hotpotqa (kilt_tasks_hotpotqa_*), natural_questions_open, openbookqa, qasc_*, quac, quail_*, quarel_*, quartz_*, quoref_*, race_high_*, race_middle_*, ropes_*, sciq_*, squad_v1.1, squad_v2.0, trivia_qa_rc, unified_qa_science_inst, web_questions_*, wiki_hop_original_*, wiki_qa_*
Natural Language Inference	anli_r1, anli_r2, anli_r3, glue_mnli, glue_rte, glue_wnli, snli, super_glue_cb, super_glue_copa, super_glue_multirc, super_glue_record, super_glue_wic, super_glue_wsc.fixed
Classification / Sentiment	ag_news_subset, amazon_polarity_*, app_reviews_*, dbpedia_14_*, glue_cola, glue_mrpc, glue_qqp, glue_sst2, imdb_reviews_plain_text, opinion_abstracts_idebate, opinion_abstracts_rotten_tomatoes, sentiment140, trec, yelp_polarity_reviews
Commonsense Reasoning	cos_e_v1.11_*, hellaswag, lambada, piqa, social_i_qa_*, story_cloze_2016, winogrande, wiqa_*
Summarization / Dialogue	aeslc, dream_*, gem_wiki_lingua_english_en, samsum, gigaword
Data-to-Text / Structured Generation	gem_common_gen, gem_dart, gem_e2e_nlg, gem_web_nlg_en, wiki_bio_*
Translation	para_crawl_enes, wmt14_translate_fr-en, wmt16_translate_cs-en, wmt16_translate_de-en, wmt16_translate_fi-en, wmt16_translate_ro-en, wmt16_translate_ru-en, wmt16_translate_tr-en
Miscellaneous / Preprocessing	definite_pronoun_resolution, fix_punct, huggingface, math_dataset_algebra__linear_1d, opinion_abstracts_*, true_case, word_segment

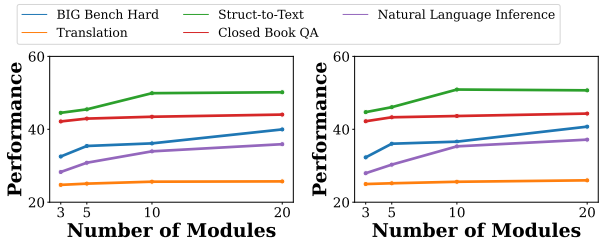
Table 6: Full list of Flan-v2 datasets used for LoRA training, grouped by task category. For brevity, "*" denotes multiple variants included in the collection.

of this choice, we compare three alternatives: using the first token, the last token, and the average across all tokens. Results are shown in Fig. 7, which presents bar plots comparing all alternatives. Across both norm- and entropy-based scoring, we observe that the performance differences between



(a) Norm (b) Entropy

Figure 7: Performance of LoGo using (a) norm and (b) entropy across datasets with different tokens for signal extraction, first, average, and last. Here, average denotes the mean signal values across all tokens. The last token serves as the default setting of our method.



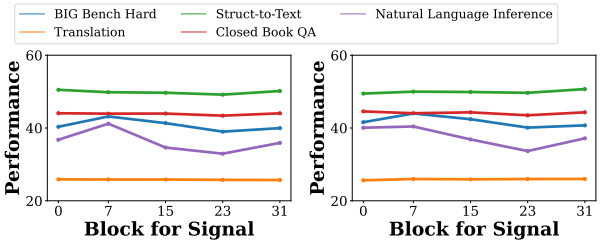
(a) Norm (b) Entropy

Figure 8: Performance of LoGo using (a) norm and (b) entropy across datasets with different numbers of selected modules.

token choices are small, indicating that LoGo is robust to this design decision. Among the three options, however, the last token consistently achieves slightly higher performance across most datasets, supporting its use as the default configuration in our method.

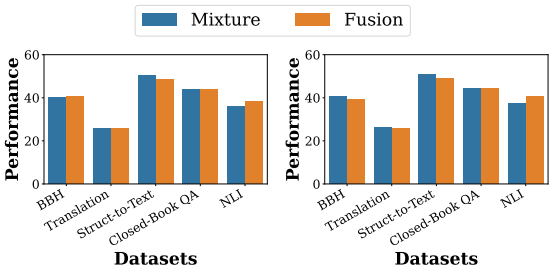
Number of Selected Modules We analyze the effect of varying the number of selected modules k in LoGo by evaluating performance with $k \in 3, 5, 10, 20$. Fig. 8 presents the results for both norm- and entropy-based scoring. Overall, performance improves as the number of selected modules increases, but the gains are relatively modest. This suggests that LoGo is not highly sensitive to the exact choice of k: even with only a few modules, it achieves performance close to the larger settings. Such robustness further highlights the practicality of LoGo, as it enables efficient operation with a small number of modules while retaining strong performance.

Block for Signal Extraction To assess the sensitivity of LoGo to the layer from which signals are extracted, we vary the target Transformer block used for signal computation. Specifically, we extract projection-based signals from the 0-th, 7-th, 15-th, 23-rd, and 31-st blocks. Results in Fig. 9 show minor variations in performance across layers, indicating that LoGo is not sensitive to the specific block chosen for signal extraction. This suggests that task-relevant activation patterns are distributed across multiple layers, and that LoGo can robustly estimate adapter relevance from various depths without requiring careful layer tuning.



(a) Norm (b) Entropy

Figure 9: Performance of LoGo using (a) norm and (b) entropy across datasets with different target block for signal extraction.



(a) Norm (b) Entropy

Figure 10: Performance of LoGo using (a) norm and (b) entropy across datasets with different merging methods – mixture and fusion.

Analysis on Merging Method LoGo adopts the mixture as merging strategy, where the projection outputs of selected adapters are combined. To assess this choice, we conduct an ablation study by replacing mixture with fusion, which merges the parameters of the selected adapters into a single set of weights before re-attaching them to the model. Results are summarized in Fig. 10, which compares the two strategies on the LLaMA-3.1-8B model across five task categories: BBH, Translation, Struct-to-Text, Closed-Book QA, and NLI. The reported results are averaged over each dataset category.

Overall, we find that mixture and fusion achieve comparable performance across all categories. However, fusion requires heavy parameter recomputation and re-attaching at the instance level, which introduces a substantial computational bur-

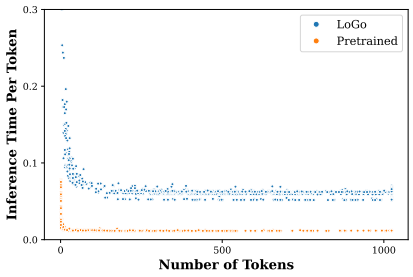


Figure 11: Inference time per token with varying numbers of tokens in CNN-DailyMail dataset samples.

den in deployment scenarios with large adapter pools. In contrast, mixture achieves similar accuracy while incurring much lower computational overhead, making it a more practical choice.

D.2 Robustness to Adapter Quality Variations

We study the robustness of LoGo to variations in adapter quality. Throughout the paper, we use adapters trained under a standardized instruction-tuning setup to enable controlled comparisons and isolate the behavior of probe-based signals.

LoGo's probe-based signals are inherently agnostic to the cause of poor performance. Adapters that are poorly trained or misaligned with the input tend to exhibit lower activation norms or higher-entropy responses, which naturally results in lower selection frequencies or reduced merging weights. As a consequence, LoGo deprioritizes low-quality adapters without supervision or task-specific signals.

To validate this behavior, we construct a mixed adapter pool containing both well-trained adapters and intentionally under-trained checkpoints. When all adapters are well trained, LoGo selects adapters from both groups at comparable rates (e.g., 57% vs. 43% on BBH tasks). In contrast, when under-trained adapters are introduced, LoGo shifts its preference strongly toward well-trained adapters (e.g., 80% vs. 20%), demonstrating robustness to noisy or uneven-quality LoRAs. While under-trained adapters are not completely suppressed, they are consistently deprioritized by the signals.

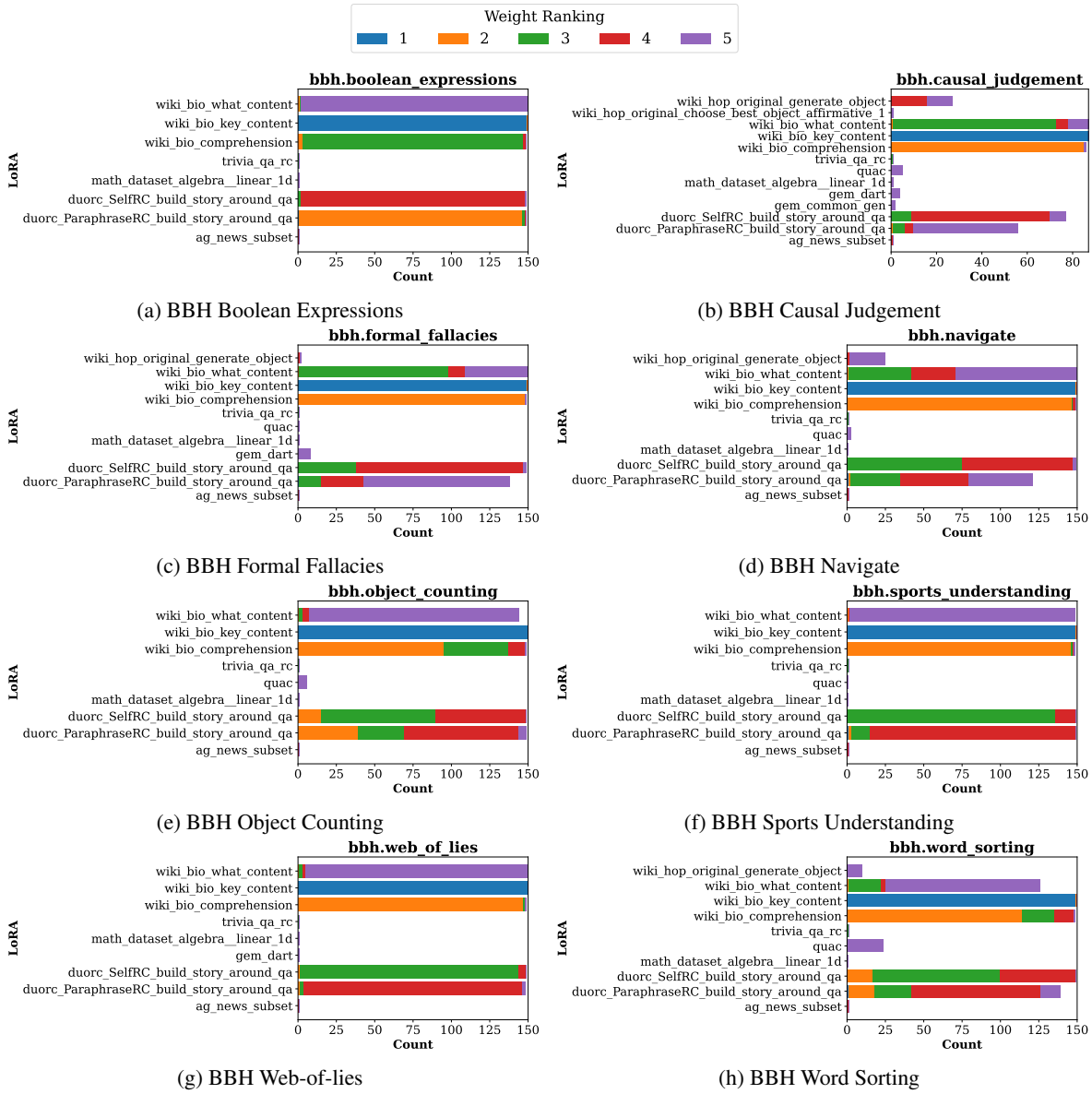
D.3 Benefits in Long Generation Task

We analyze how the computational overhead of LoGo behaves in long text generations. Experiments are conducted on the **CNN-DailyMail** (See et al., 2017) dataset using the LLaMA-3.1-8B model with an NVIDIA H200 GPU. We measure the inference time per token as a function of the number of generated tokens, and compare LoGo against the pretrained model.

As shown in Figure 11, the per-token inference time of LoGo decreases rapidly as the number of generated tokens increases, stabilizing after approximately 100 tokens. While a gap remains between LoGo and the pretrained model, this difference reflects the intrinsic overhead of employing LoRA adapters. These results indicate that the cost of signal extraction at the beginning of generation is effectively amortized over longer sequences.

D.4 Selected LoRAs

Figures 12 to 16 show the LoRA adapter selection counts by our proposed method, LoGo, with LLaMA-3.1-8B model for various datasets.



(a) BBH Boolean Expressions

(b) BBH Causal Judgement

(c) BBH Formal Fallacies

(d) BBH Navigate

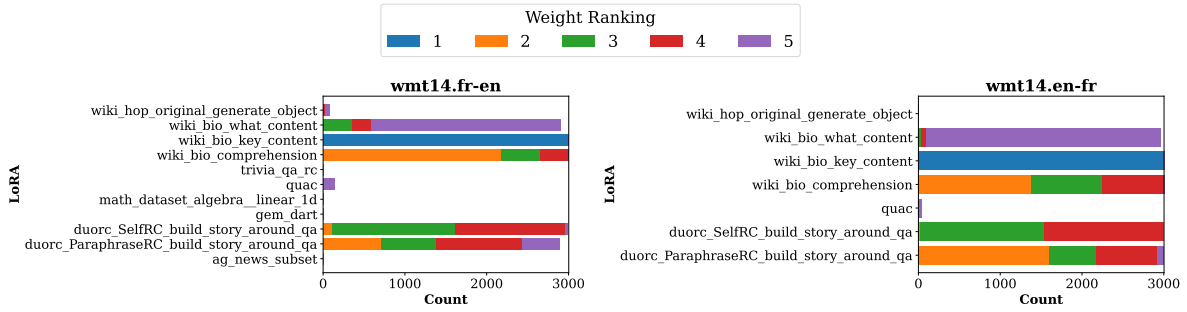
(e) BBH Object Counting

(f) BBH Sports Understanding

(g) BBH Web-of-lies

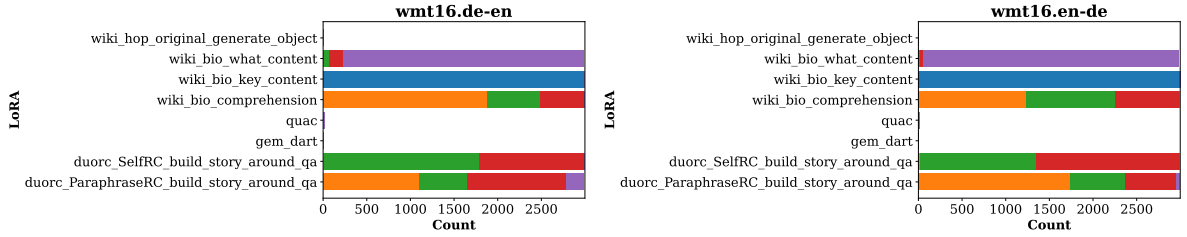
(h) BBH Word Sorting

Figure 12: The LoRA selection count by LoGo with LLaMA-3.1-8B model for BIG Bench Hard datasets.



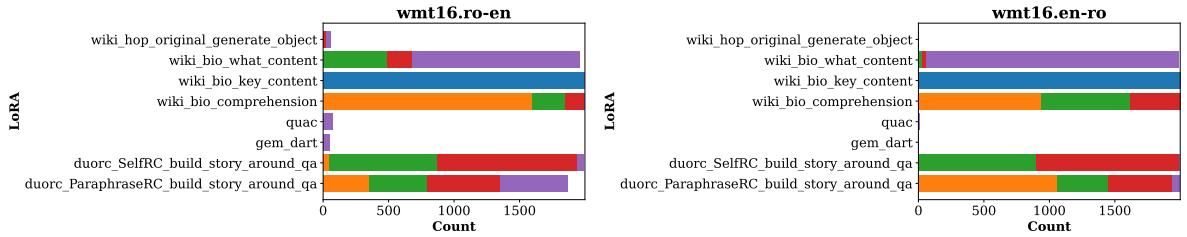
(a) WMT'14 FR->EN

(b) WMT'14 EN->FR



(c) WMT'16 DE->EN

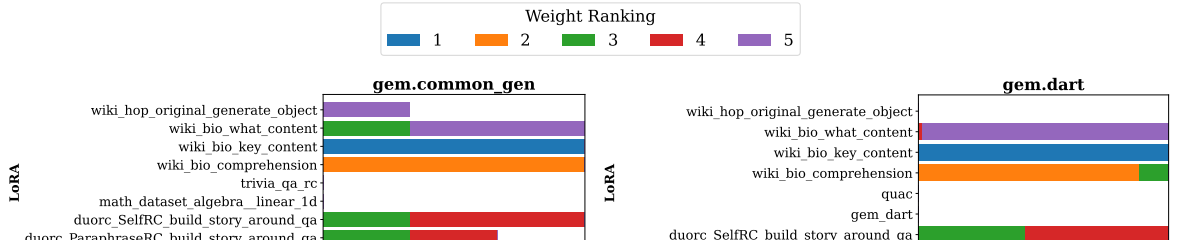
(d) WMT'16 EN->DE



(e) WMT'16 RO->EN

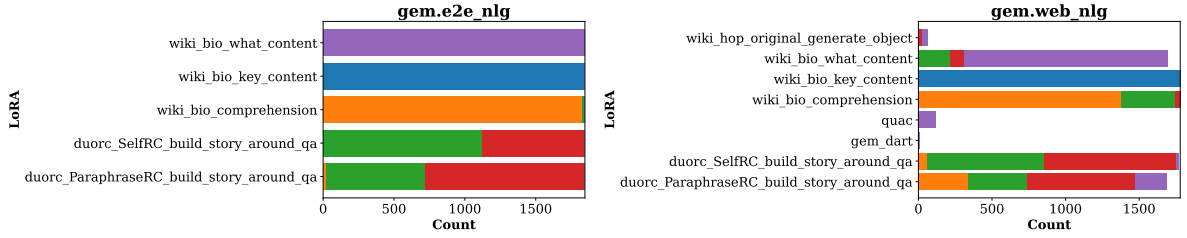
(f) WMT'16 EN->RO

Figure 13: The LoRA selection count by LoGo with LLaMA-3.1-8B model for translation datasets.



(a) CommonGen

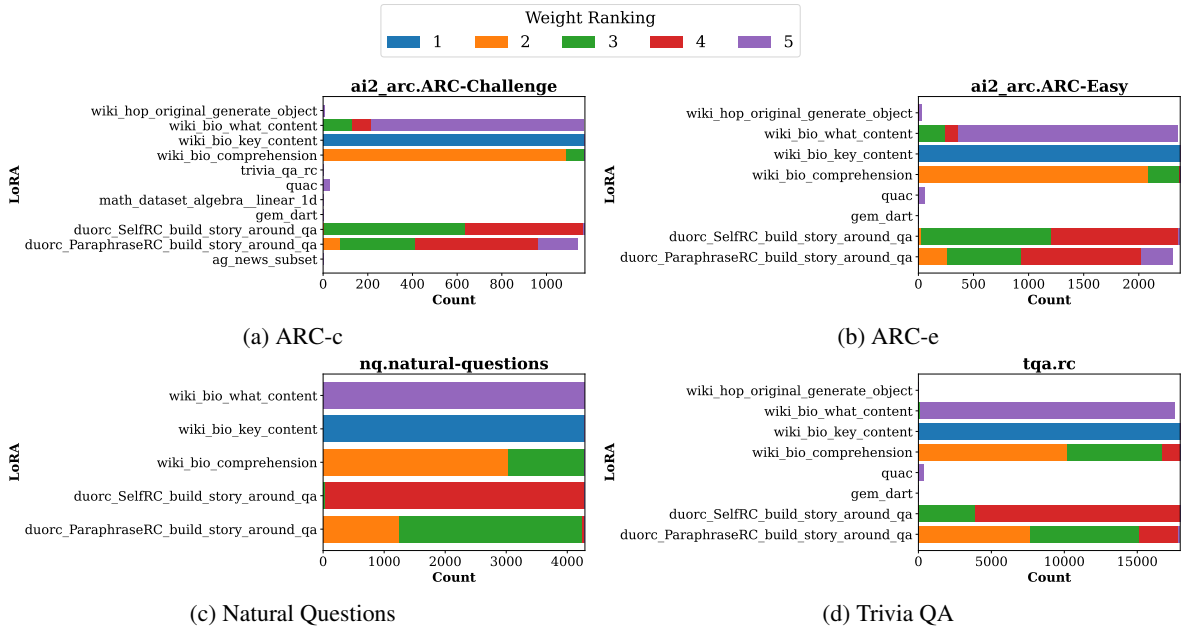
(b) DART



(c) E2ENLG

(d) WebNLG

Figure 14: The LoRA selection count by LoGo with LLaMA-3.1-8B model for struct-to-text datasets.



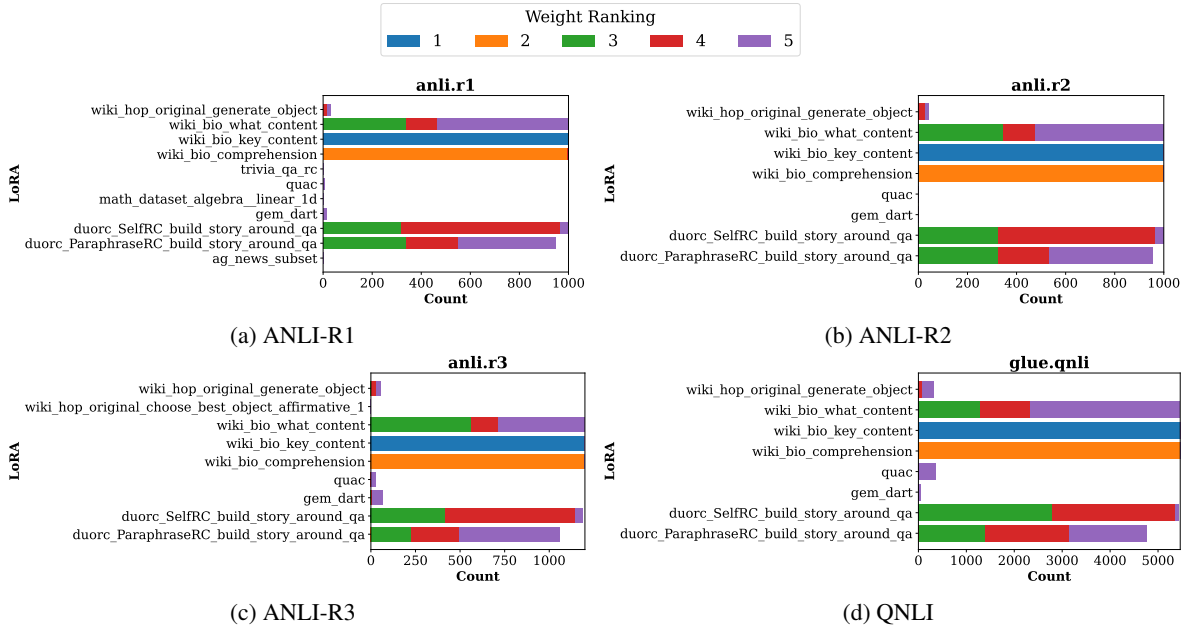
(a) ARC-c

(b) ARC-e

(c) Natural Questions

(d) Trivia QA

Figure 15: The LoRA selection counts by LoGo with LLaMA-3.1-8B model for closed-book QA datasets.



(a) ANLI-R1

(b) ANLI-R2

(c) ANLI-R3

(d) QNLI

Figure 16: The LoRA selection counts by LoGo with LLaMA-3.1-8B model for NLI datasets.