

# Speciality vs Generality: An Empirical Study on Catastrophic Forgetting in Fine-tuning Foundation Models

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## Abstract

Foundation models, including Vision Language Models (VLMs) and Large Language Models (LLMs), possess the *generality* to handle diverse distributions and tasks, which stems from their extensive pre-training datasets. The fine-tuning of foundation models is a common practice to enhance task performance or align the model’s behavior with human expectations, allowing them to gain *speciality*. However, the small datasets used for fine-tuning may not adequately cover the diverse distributions and tasks encountered during pre-training. Consequently, the pursuit of speciality during fine-tuning can lead to a loss of generality in the model, which is related to catastrophic forgetting (CF) in deep learning. In this study, we demonstrate this phenomenon in both VLMs and LLMs. For instance, fine-tuning VLMs like CLIP on ImageNet results in a loss of generality in handling diverse distributions, and fine-tuning LLMs like Galactica in the medical domain leads to a loss in following instructions and common sense.

To address the trade-off between the speciality and generality, we investigate multiple regularization methods from continual learning, the weight averaging method (Wise-FT) from out-of-distributional (OOD) generalization, which interpolates parameters between pre-trained and fine-tuned models, and parameter-efficient fine-tuning methods like Low-Rank Adaptation (LoRA). Our findings show that both continual learning and Wise-FT methods effectively mitigate the loss of generality, with Wise-FT exhibiting the strongest performance in balancing speciality and generality.

## 1 Introduction

Foundation models, such as CLIP [59] for vision-language models (VLMs) and GPT-3 [7] for large language models (LLMs), have garnered widespread attention due to their remarkable achievements. These models are pre-trained on vast datasets, which endows them with an impressive level of

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**generality** [6]. They exhibit the ability to effectively handle diverse distributions and tasks, as illustrated by CLIP’s exceptional performance on ImageNet and its variants with distributional shifts. Similarly, GPT-3 showcases its prowess in various tasks such as translation, common sense question-answering, and cloze tasks.

The generality of foundation models can be categorized into two aspects. Firstly, *task generality* highlights the ability of foundation models to handle diverse tasks. For example, an LLM is proficient in instruction-following as well as question-answering (QA) on common sense. Secondly, *distribution generality* emphasizes the capability of foundation models to accommodate different data distributions within a given task. For instance, VLMs like CLIP demonstrate their proficiency in classifying both ImageNet [18] containing natural photos, and ImageNet-Sketch [77] containing sketches. Another illustration of distribution generality is the LLM’s competence in performing medical question-answering tasks on distinct datasets such as MedQA-USMLE [52] containing medical subject questions, and MedMCQA [33] containing real-world medical consultation questions.

It is a common practice to fine-tune foundation models on specific tasks to enhance task performance or align the model’s behavior with human expectations. During the fine-tuning stage, the foundation models gain **speciality** to achieve exceptional performance on the fine-tuning task. However, since the small fine-tuning dataset does not have sufficient coverage of the distribution as well as tasks, the fine-tuned model can potentially lose its generality. This phenomenon is closely associated with the concept of catastrophic forgetting (CF) observed in deep neural networks (DNN). Previous studies have revealed that when learning new tasks, DNNs have the potential to forget their proficiency in previously learned tasks.

In this work, we aim to answer the following question:

- *Does the foundation model forget generality when being fine-tuned to gain the speciality for a specific task?*
- *If so, what method can mitigate the speciality-generality tradeoff?*

To address the aforementioned questions comprehensively, we perform experiments utilizing CLIP for VLMs and Galactica [72] for LLMs. For CLIP, we investigate distribution generality forgetting by conducting two experiments. Firstly, we fine-tune CLIP on the ImageNet dataset and evaluate its distribution generality on the ImageNet variants. Secondly, we fine-tune CLIP on the ‘real’ domain of DomainNet and assess its distribution generality on other domains within DomainNet. In the case of Galactica, we fine-tune it on a specific dataset within the medical question-answering (QA) task. Subsequently, we measure its distribution generality across other medical QA datasets and evaluate its task generality in common sense QA as well as instruction following tasks. See Section 3 for more details on the experimental settings.

In Section 4, our findings provide a positive response to the first question, showing a trade-off between speciality and generality during fine-tuning. More specifically, the fine-tuned models exhibit notable speciality by achieving exceptional performance on the fine-tuning dataset. However, they demonstrate inferior performance compared to the pre-trained model in terms of generality, including both distribution and task generality. For instance, the performance of CLIP on the ImageNet variants and Galactica on the instruction following task experiences a significant decline.

To address the second question, we conduct a systematic investigation of various methods developed across different communities. Let’s denote the model as  $f_\theta$  with parameter  $\theta$ , and use  $\theta_0$  to represent the pre-trained parameter. We explore the following methods:

- Continual learning methods: These methods involve regularizing the fine-tuned parameter  $\theta$  towards  $\theta_0$ . We consider adding L1 penalty  $|\theta - \theta_0|$  [53] and L2 penalty  $\|\theta - \theta_0\|_2^2$  [82]. We also examine the knowledge distillation (KD) method, which enforces the output of  $f_\theta$  to remain close to  $f_{\theta_0}$  through the penalty  $\|f_\theta(\mathbf{x}) - f_{\theta_0}(\mathbf{x})\|_2^2$  [42], where  $\mathbf{x}$  represents the input.
- Out-of-distributional (OOD) generalization methods: We consider approaches such as Wise-ft [80] which uses  $f_{\alpha\theta_0 + (1-\alpha)\theta}$  by interpolating between  $\theta$  and  $\theta_0$ , where  $\alpha$  is between 0 and 1.
- Parameter-efficient fine-tuning methods: We investigate techniques like LoRA [28], which utilize low-rank matrix re-parameterize the update  $\theta - \theta_0$ .

Our further results in Section 4 provide an affirmative answer to the second question by showing that the L1/L2/KD as well as Wise-ft can effectively mitigate catastrophic forgetting and preserve generality during fine-tuning. Among them, Wise-ft achieves the best performance on speciality-generality trade-off.

We summarize our main findings as follows:

- In our systematic experiments on both VLMs and LLMs, we have observed clear instances where the foundation models tend to forget their generality during the fine-tuning process to gain speciality for a specific task. Notably, the forgetting of LLM is more severe on the tasks that is significantly different from the fine-tuning task.
- Continual learning methods such as L1, L2, and KD penalty can effectively mitigate generality forgetting compared to vanilla fine-tuning, while still achieving reasonable performance on the fine-tuned task.
- The model averaging method, Wise-ft, demonstrates the strongest performance in balancing pre-trained generality and fine-tuned speciality across various scenarios.
- LoRA excels in mitigating forgetting and even surpasses Wise-ft when it can effectively solve the fine-tuning task, but it performs poorly compared to other methods when the task is challenging for LoRA.

## 2 Related Works

**Foundation Models.** Foundation models, including Vision-and-Language Models (VLMs) and Large Language Models (LLMs), are pre-trained using vast amounts of data. While the underlying technology for pre-training these models, such as deep neural networks trained through self-supervised methods on extensive datasets, is not novel, their remarkable capability to generalize and adapt to diverse downstream tasks is unprecedented [6]. An excellent line of VLMs includes CLIP [59], ALIGN [31], BASIC [56] and BLIP [40]. The LLMs include many excellent works, to

name a few, GPT [7], LLaMA [75], Galactica [72], Bloom [67]. It is a common practice to fine-tune the foundation model to obtain better performance on a specific task [20], follow the instruction of humans [51, 66, 79] and aligns with humans’ preferences [3, 51, 21].

**Pretraining, fine-tuning, and distributional shift.** Before the emergence of foundation models, the pre-training and fine-tuning paradigm had already achieved remarkable accomplishments across numerous applications [25, 59, 19]. However, when deploying pre-trained models into real-world applications and fine-tuning them, a common challenge arises: encountering novel samples from a target distribution that differs from the fine-tuning distribution [2, 23, 84, 43, 88, 89, 44, 70]. To address this issue, several approaches have been proposed. For instance, [80, 12, 15] suggest leveraging the weight ensemble of the pre-trained model and the fine-tuned model to enhance out-of-distribution (OOD) performance. Another strategy, as proposed in [38], is the LP-FT technique, which involves initializing the pre-trained feature extractor with a reasonably good classifier. This initialization is particularly important when the classifier is randomly initialized, as the pre-trained features can easily be distorted to accommodate the random classifier during fine-tuning, exacerbating the issue of catastrophic forgetting.

**Catastrophic forgetting and continual learning.** DNN tends to lose the knowledge of previously learned task (e.g., pretraining task) when it begins to learn a new task (e.g., the fine-tuning task) [50]. Various attempts have been made to alleviate catastrophic forgetting. [82, 64, 1, 68] imposes a penalty on the change of the parameter on the new task. [37] gains intuition from Taylor expansion of the losses of the old task at the point of fine-tuned parameter, and further proposes EWC by incorporating the Hassien matrix into parameter regularization. The reply-based method tries to approximate and recover the old data distribution. Popular methods in this direction include sampling methods which store a few old training samples with a small memory buffer [76, 63, 13, 11, 9], and generative methods which generate samples from the old distributions with a generative model [10]. Knowledge distillation (KD) methods try to keep the prediction of the fine-tuned model close to that of the old model. KD can be naturally combined with experience reply. For example, [61] proposes to perform KD on the samples of new tasks as well as the old samples stored in the buffer.

Notably, previous continual learning focus on sequentially learning tasks which learns a sequence of task in order and measure the forgetting of older tasks when learning new tasks [78]. Whereas, we focus on the generality forgetting of the pre-trained foundation model during fine-tuning a specific task. Refer to Section A.2 for a detailed discussion.

## 3 Experimental Settings and Methods

### 3.1 Settings

Consider that the foundation model has been pre-trained on massive data, containing  $M$  tasks  $\{\mathcal{T}^1, \mathcal{T}^2, \dots, \mathcal{T}^M\}$ . Denote the pre-trained foundation model as  $f_{\theta_0}$  where  $\theta_0$  is the model parameter.

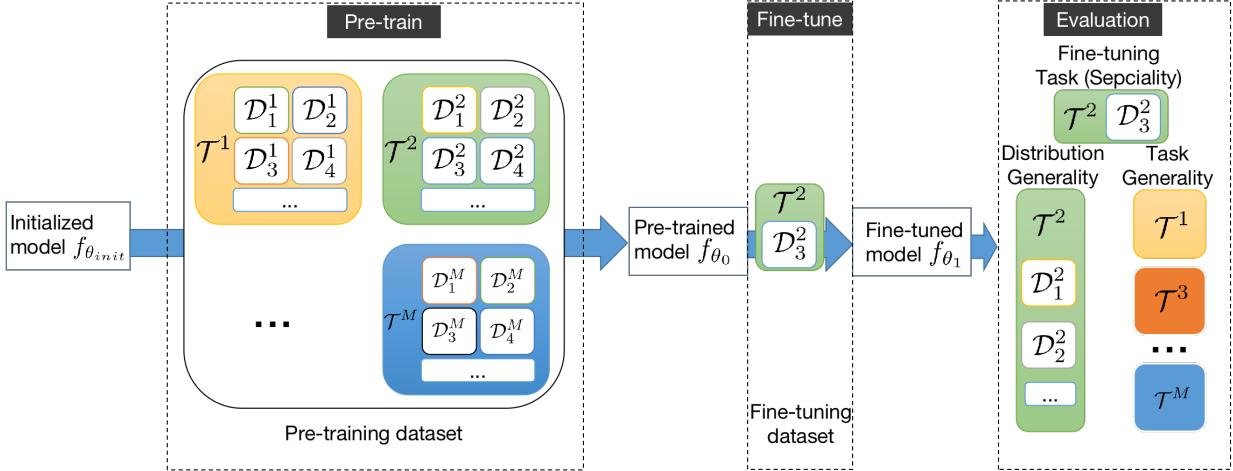


Figure 1: Our setting to investigate the CF of the generality in pre-trained foundation model.

Each task  $\mathcal{T}^i$  consists of instances of  $\mathbf{z}$ . For LLMs,  $\mathbf{z} = \mathbf{x}$  is the auto-regressive language tokens; and for VLMs,  $\mathbf{z} = (\mathbf{x}, \mathbf{y})$  contains a pair of image input  $\mathbf{x}$  and language label  $\mathbf{y}$ . See Appendix A.1 for more discussion on the definition of tasks. Since the pre-training dataset covers a variety of distributions for each task, we consider that a task  $\mathcal{T}^i$  contains samples from  $N^i$  domains, i.e.,  $\mathcal{T}^i = \{\mathcal{D}_j^i\}_{j=1}^{N^i}$ , where  $\mathcal{D}_j^i$  represents the samples  $\mathbf{z}$  from the distribution  $\mathbb{P}_j^i(\mathbf{z})$  and the distributions of different domains in the same task differs from each other, i.e.,  $\mathbb{P}_j^i(\mathbf{z}) \neq \mathbb{P}_k^i(\mathbf{z})$  for  $j \neq k$ . We consider the following two types of catastrophic forgetting (CF) when fine-tuning foundation models

- Distribution generality forgetting. When the foundation model is finetuned on  $\mathcal{D}_j^i$ , i.e., the  $j$ th domain of task  $\mathcal{T}^i$ , it may forget the rest domains of task  $\mathcal{T}^i$ , i.e.,  $\{\mathcal{D}_k^i\}_{k \neq j}$ . We are interested in the performance of the fine-tuned foundation model on the  $\{\mathcal{D}_k^i\}_{k \neq j}$ .
- Task generality forgetting. When the foundation model is finetuned on the domain  $\mathcal{D}_j^i$  of task  $\mathcal{T}^i$ , we are interested in the performance in the other tasks, i.e.,  $\{\mathcal{T}^k\}_{k \neq i}$ .

### 3.1.1 Vision Language Models

For VLMs, we investigate the CLIP, a famous vision-language model. CLIP can perform zero-shot classification on a wide range of datasets, showing a strong ability to generalize a variety of data distributions. However, the performance of CLIP can still be inferior on a specific task, especially on the task whose relevant data is insufficient in the training dataset of CLIP [87]. Therefore, CLIP needs to be fine-tuned to enhance the downstream task performance. Since the fine-tuning dataset does not have sufficient coverage of the data distributions, the fine-tuning process can weaken the robustness of CLIP to the distributional shift. For example, fine-tuning CLIP on the domain  $\mathcal{D}_j^i$  of task  $\mathcal{T}^i$  can significantly boost the performance on  $\mathcal{D}_j^i$ , whereas, potentially leads to worsened OOD performance on  $\{\mathcal{D}_k^i\}_{k \neq j}$ . This phenomenon has been studied in OOD literature [80, 24, 74, 45], whereas few work has studied it in the context of catastrophic forgetting.

Following [80, 24, 74, 45], we conduct experiments on the following two settings:

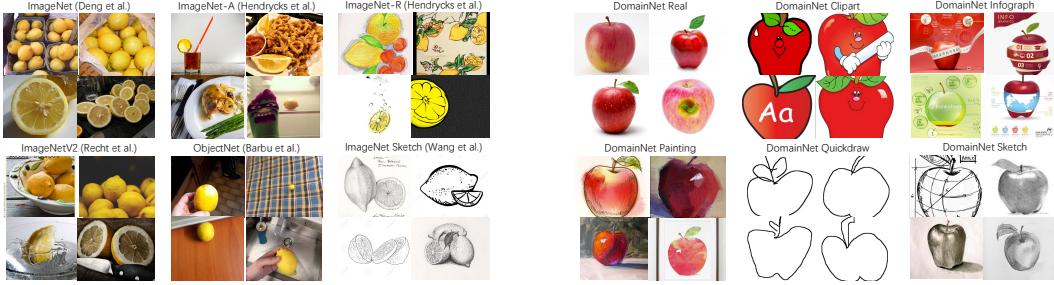


Figure 2: (Left) Illustration samples of the class lemon from ImageNet and 5 variants; (Right) Illustration samples of the class apple from DomainNet.

- (a) Fine-tune CLIP on ImageNet and evaluate the forgetting on five variants of ImageNet with distributional shifts. Specifically, we consider the task  $\mathcal{T}^1$  to perform classification in ImageNet. We fine-tune  $f_{\theta_0}$  on ImageNet i.e.,  $\mathcal{D}_1^1$ , and evaluate the distribution generality forgetting on  $\{\mathcal{D}_i^1\}_{i=2}^6$ , five variants of ImageNet with natural shifts (ImageNet-V2[62], ImageNet-R[26], ImageNet Sketch[77], ObjectNet[4], and ImageNet-A[27]).
- (b) Fine-tune CLIP on the “real” domain of DomainNet [55] and assess the extent of CF on the other domains in DomainNet. The DomainNet dataset represents the task  $\mathcal{T}^1$ , where the “real” domain corresponds to the fine-tuned domain  $\mathcal{D}_1^1$ , while the remaining domains in DomainNet, namely “Clipart”, “Infograph”, “Painting”, “Quickdraw”, and “Sketch”, are utilized as the testing domains.

We use CLIP with VIT-16/B pre-trained by OpenAI. We include more details on the experiments in Appendix E. In the VLM part, our primary focus revolves around investigating the issue of distribution generality forgetting [80, 24, 74, 45] (not task generality). This is because models like CLIP, which are fine-tuned for specific classification tasks, are unlikely to encounter samples from other classes (other tasks) during deployment. For instance, if we fine-tune CLIP to distinguish between cats and dogs, we would not expect this model to classify camels when deployed. However, when it comes to LLM, we face a different scenario. Let’s take the example of training a chat robot for medical purposes. When fine-tuning the LLM for the task of medical knowledge, it is also crucial for the LLM to possess the ability to understand and follow human instructions, which inherently involve distinctly different tasks apart from the medical domain itself. Therefore, in the context of LLM, we will address both the issues of distribution generality forgetting and task generality forgetting to ensure its overall competence and versatility.

### 3.1.2 Large Language Models

For LLMs, we adopt Galactica-1.3B [72] and conduct experiments with the LMFlow framework <sup>1</sup> [20]. As discussed before, consider a language model tuned for the medical domain, it should have expertise in the medical task, and also be able to perform different tasks such as instruction following.

<sup>1</sup><https://github.com/OptimalScale/LMFlow>

Therefore, we investigate the scenario to fine-tune Galactica on QA task  $\mathcal{T}^1$ . Specifically, we fine-tune the model on a medical question-answer (QA) dataset, i.e., using MedMCQA [52] as  $\mathcal{D}_1^1$ . MedMCQA is here. We evaluate the forgetting of the pre-trained model in the following aspects:

- Evaluate the distribution generality forgetting on the other medical datasets containing distributional shift. Sepcifically, we use PubMedQA [34] and MedQA-USMLE [33] as  $\mathcal{D}_2^1$  and  $\mathcal{D}_3^1$ . We refer PubMedQA [34] and MedQA-USMLE [33] as Medical OOD datasets in the following discussion.
- Evaluate the task generality by forgetting the following aspects:
  - Common sense QA task  $\mathcal{T}^2$ , which contains four datasets  $\{\mathcal{D}_i^2\}_{i=1}^4$ , namely, ARC Easy [16] and Challenge on [16] science exams, Race [39] on Reading Exams and PIQA [5] on physical interaction. dMCQA focus on the medical domain.
  - Instruction following task  $\mathcal{T}^3$ , which containing 3 datasets  $\{\mathcal{D}_i^3\}_{i=1}^3$ , namely, Alpaca [71], GPT4 instruct [54] and LMFlow [20].

The performance of the QA task is evaluated by the accuracy and the performance of the instruction following is evaluated by log-likelihood (LL), whose details are in Appendix B. We also give illustrations of each dataset in Table 1.

Notably, the conceptual distance between the fine-tuning dataset MedMCQA and the Medical OOD datasets, Common Sense QA datasets, and instruction following datasets indeed increases.

- The Medical OOD datasets are relatively close to MedMCQA since they both involve medical QA tasks. This similarity in domain makes them conceptually closer.
- On the other hand, the Common Sense QA datasets have a larger distance from MedMCQA compared to the Medical OOD datasets. While all these datasets involve QA tasks with choices (A/B/C), Common Sense QA focuses specifically on the common sense domain, which differs from the medical domain of MedMCQA. This difference in domain knowledge contributes to a greater conceptual distance.
- Additionally, the instruction following datasets have a larger distance from MedMCQA. This is because the instruction following datasets contain samples with general instructions, rather than choice QA questions (A/B/C), which is the format of MedMCQA.

Figure 3 summarizes the conceptual distance between MedMCQA and the Medical OOD datasets, Common Sense QA datasets, and instruction following datasets.

## 3.2 Methods

### 3.2.1 Regularization towards Pretrained Weight

Let's recall that  $\theta_0$  represents the parameters of the pre-trained foundation model. To address the issue of catastrophic forgetting (CF) during fine-tuning, a straightforward approach is to enforce a

Task Type	Dataset Name	Example
Medical	PubMedQA [34]	<p><i>Context:</i> Middle third clavicular fracture ... ?</p> <p><i>Question:</i> Does comminution play no role in treated middle third clavicular fracture?</p> <p><i>Output:</i> yes</p>
	MedMCQA [52]	<p><i>Question:</i> Severe painful sensorimotor and autonomic neuropathy along with alopecia may suggest poisoning with:            (A) Thallium (B) Arsenic (C) Lead (D) Copper.</p> <p><i>Output:</i> A</p>
	MedQA-USMLE [33]	<p><i>Question:</i> A 23-year-old pregnant woman at 22 weeks...            Which of the following is the best treatment for this patient?            (A) Ampicillin, (B) Ceftriaxone,            (C) Doxycycline, (D) Nitrofurantoin.</p> <p><i>Output:</i> B</p>
Common Sense	ARC Easy [16]	<p><i>Question:</i> What carries oxygen throughout the body?            (A) white blood cells, (B) brain,            (C) red blood cells, (D) nerves</p> <p><i>Output:</i> C</p>
	ARC Challenge [16]	<p><i>Question:</i> Which technology was developed most recently?            (A) cellular telephone, (B) television,            (C) refrigerator, (D) airplane.</p> <p><i>Output:</i> A</p>
	Race [39]	<p><i>Passage:</i> The rain had continued for a week, ...</p> <p><i>Question:</i> What did Nancy try to do before she fell over?            (A) Measure the depth, (B) Look for a tree trunk,            (C) Protect her cows, (D) Run away</p> <p><i>Answer:</i> C</p>
	PIQA [5]	<p><i>Goal:</i> When boiling butter, when it's ready, you can            (Sol1) Pour it onto a plate, (Sol2) Pour it into a jar,</p> <p><i>Answer:</i> Sol1</p>
Instruction	Alpaca [71]	<p><i>Instruction:</i> Give three tips for staying healthy.</p> <p><i>Output:</i> 1. Eat a balanced diet. 2. Exercise regularly. 3. ....</p>
	GPT4 instruct [54]	<p><i>Input:</i> Compare and contrast the effects of individual ...?</p> <p><i>Output:</i> Individual performance refers to ...</p>
	LMFlow [20]	<p><i>Human:</i> I think the biggest thing is that it's in her smile.</p> <p><i>Assistant:</i> That sounds very comforting...</p> <p><i>Human:</i> Ok, can you remind me to change scenes ?</p> <p><i>Assistant:</i> Sure, it's important to change scenes every ...</p>

Table 1: Illustrations of datasets of medical QA tasks(PubMedQA, MedMCQA, MedQA-USMLE), common sense QA tasks(ARC Easy/Challenge, Race, PIQA), and instruction following tasks(Alpaca, GPT4 instruct, LMFlow).

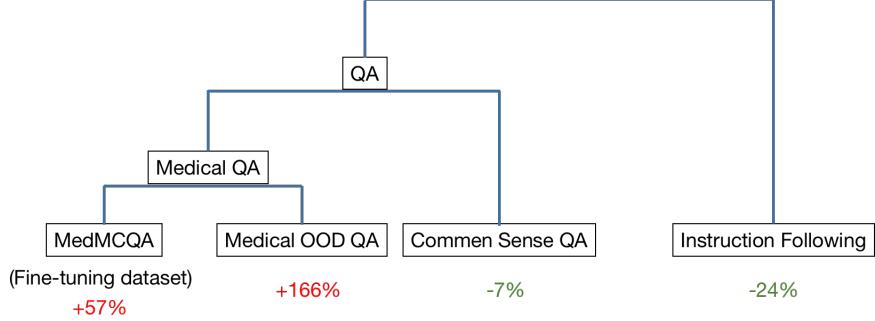


Figure 3: Illustration of the conceptual distance and the corresponding performance (relative) change of fine-tuning Galactica on MedMCQA.

constraint on the proximity of  $\theta$  to  $\theta_0$ . In other words, we ensure that  $\theta$  does not deviate too far from  $\theta_0$  [82]. We accomplish this by optimizing two penalties:

- The L1 penalty  $|\theta - \theta_0|$  [53]<sup>2</sup>,
- The L2 penalty  $\|\theta - \theta_0\|_2^2$  [82].

It is worth noting that the L1 penalty tends to produce sparse solutions, indicating that  $\theta$  can only differ from  $\theta_0$  in a limited subset of parameters [86].

### 3.2.2 Parameter-efficient Fine-tuning

Parameter-efficient fine-tuning aims to achieve comparable performance as traditional fine-tuning while utilizing significantly fewer trainable parameters. One widely adopted method in this domain is LoRA (Low-Rank Adaptation) [28], which effectively represents modified weights  $\Delta\theta$  using low-rank matrix pairs while keeping most of the pre-trained network parameters frozen. This approach has shown performance on par with full fine-tuning.

In our study, we apply LoRA specifically to two weight matrices ( $W_q$  and  $W_v$ ) within the self-attention module of the Transformer architecture. We constrain the update of a pre-trained weight matrix  $\Delta\theta_0 = \theta - \theta_0 \in \mathbb{R}^{d \times k}$  by representing the updated portion as  $\Delta\theta = BA$ , where  $B \in \mathbb{R}^{d \times r}$ ,  $A \in \mathbb{R}^{r \times k}$ , and the rank  $r$  is much smaller than  $\min(d, k)$ . We explore different values of  $r$  as a hyper-parameter. During training,  $\theta_0$  remains fixed, and only  $A$  and  $B$  receive gradient updates. We initialize  $A$  with random Gaussian values and set  $B$  to zero.

### 3.2.3 Knowledge Distillation

Knowledge distillation involves transferring knowledge from a larger model (teacher) to a smaller one (student). In our case, we aim to preserve the generality of the pre-trained model during the fine-tuning process. We utilize the pre-trained model  $f_{\theta_0}$  as the teacher and the fine-tuned model  $f_\theta$

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<sup>2</sup>[53] applies a post-processing technique to find the sparsity structure in the  $\theta - \theta_0$ . For simplicity, we use the L1 norm to encourage sparsity [86]. This method is also connected with parameter-efficient fine-tuning. We put it in the category of continual learning since it is close to the penalty  $\|\theta - \theta_0\|_2^2$  [82].

as the student. To ensure the student model’s predictions or learned features align closely with those of the teacher model, we enforce an L2 regularization constraint on their outputs:  $\|f_\theta(\mathbf{x}) - f_{\theta_0}(\mathbf{x})\|_2^2$  [8, 29].

### 3.2.4 Model Averaging

The model averaging method, Wise-ft, introduced in [80], suggests a linear interpolation approach between the pre-trained parameter  $\theta_0$  and the fine-tuned parameter  $\theta$ . This results in the model  $f_{(1-\alpha)\theta_0+\alpha\theta}$ , where  $\alpha$  represents a hyper-parameter ranging from 0 to 1.

## 4 Results

### 4.1 Vision Language Models

The results of CLIP are presented in Figure 4. The left and right panels of Figure 4 showcase the outcomes of fine-tuning CLIP on ImageNet and DomainNet, respectively. It can be observed that fine-tuning leads to lower generality performance compared to the original pre-trained model. Although this phenomenon has been studied within the OOD community, its direct connection to catastrophic forgetting (CF) remains unclear. In Appendix C, we provide explicit evidence that this phenomenon is closely associated with representation forgetting [42, 37, 32, 17, 78, 83], which is a common form of CF. Figure 4 provides a comparison of different methods for fine-tuning CLIP. The following observations can be made:

- Continual learning methods such as L1, L2, and KD penalty all show improvement in distribution generality performance, indicating that distribution generality forgetting can be mitigated by simple continual learning techniques.
- Wise-ft stands out as it significantly alleviates distribution generality forgetting and achieves the best distribution generality performance. In ImageNet, Wise-ft surpasses both the trained and fine-tuned models, as well as methods like L1/L2/LORA/KD, with the highest distribution generality performance exceeding 63%. None of the other methods achieve a distribution generality performance better than 62%. The trend observed in DomainNet is similar to that in ImageNet.
- The KD method achieves better speciality performance than Wise-ft while maintaining a relatively high distribution generality performance. Specifically, KD and Wise-ft are comparable to each other, and there is no consistent superiority of one over the other.
- The trade-off of LoRA is inferior compared to other methods on VLMs. We note that LoRA can not match the full fine-tuning performance on speciality performance.

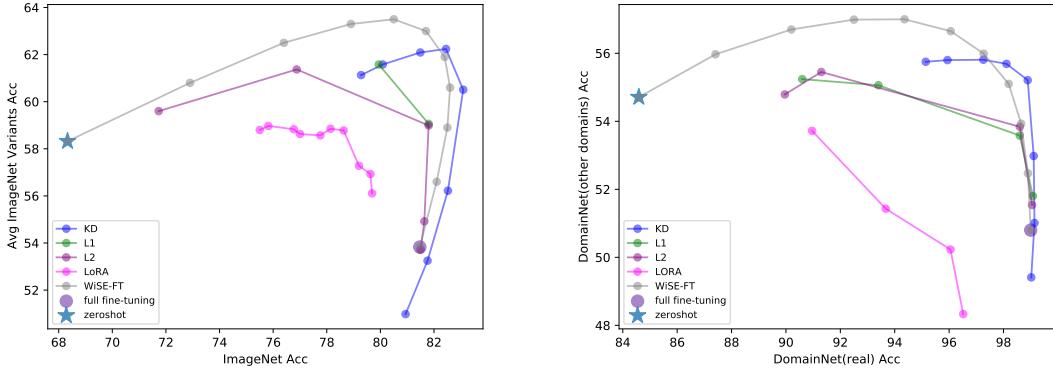


Figure 4: On the speciality and generality trade-off of fine-tuning CLIP. Left) fine-tune on ImageNet and evaluate the generality by the average performance of ImageNet variants, i.e., ImageNet-V2, ImageNet-R, ImageNet Sketch, ObjectNet, and ImageNet-A; Right) fine-tune on the ‘real’ domain of DomainNet and evaluate the generality by the average performance on the Clipart”, “Infograph”, “Painting”, “Quickdraw”, and “Sketch” domains.

## 4.2 Large Language Models

Figures 5 and 6 show the results of fine-tuning Galactica on MedMCQA and PubMedQA, respectively. The main results are as follows:

- We did not observe consistent distribution generality forgetting when fine-tuning various medical datasets. Specifically, when fine-tuning MedMCQA, we noted that the performance on the other two datasets from the medical domain, namely PubMedQA and MedQA-USMLE, actually improved simultaneously. However, the opposite effect was observed when fine-tuning PubMedQA, as the performance on MedMCQA and MedQA-USMLE decreased. We observe consistent task generality forgetting on Common Sense datasets and Instruction following datasets in both Figure 5 and 6. For example, Figure 5(c) shows that the log-likelihood of instruction tasks drops from about -255 to -310 as we fine-tune Galactica on MedMCQA; Figure 6(c) shows the instruction performance drops to less than -290 when we fine-tune Galactica on PubMedQA.
- **Larger conceptual distance, more severe forgetting.** The results in Figure 5(a)-(c) show that larger conceptual distance leads to more severe forgetting in the LLM. The conceptual distances between MedMCQA and other datasets (OOD medical tests, Common Sense QA, and instruction following) are discussed in Section 3.1.2 and illustrated in Figure 3. In Figure 5(a), the task with the smallest conceptual distance (OOD medical) exhibits no forgetting, indicating that the LLM retains its performance on conceptually similar tasks. However, Figure 5(c) reveals significant forgetting (over 20% drop) in the task with the largest conceptual distance (instruction following). This suggests that the LLM struggles more with tasks that are further away conceptually from the fine-tuning task. The Common Sense QA task

falls between the OOD medical and instruction following tasks in terms of forgetting, as shown in the results. These findings highlight that the LLM’s forgetting behavior is influenced by the conceptual distance between the fine-tuning task (MedMCQA) and other tasks. Tasks closer in concept to MedMCQA experience less forgetting, while tasks with larger conceptual distances are more prone to forgetting.

- **Model averaging methods achieves strong performance.** Wise-ft [80] consistently addresses the issue of forgetting common sense and instructions. For instance, in Figure 5(c), it is demonstrated that using Wise-ft with  $\alpha = 0.3$  effectively enhances the log-likelihood (LL) score, raising it above -270, even when the performance on the fine-tuning dataset remains relatively unchanged. Similarly, in Figure 6(c), Wise-ft with  $\alpha = 0.3$  improves the LL score from about -290 to approximately -270.
- **The effectiveness of LoRA.** The performance of LoRA varies significantly depending on whether it is fine-tuned on MedMCQA or PubMedQA. Specifically, LoRA demonstrates remarkable mitigation of forgetting in instruction following when fine-tuning on PubMedQA, surpassing even the performance of Wise-ft (e.g., Figure 6(C)). However, LoRA performs poorly compared to Wise-ft and other methods on MedMCQA (e.g., Figure 5(C)). One notable distinction in LoRA’s performance between PubMedQA and MedMCQA is that LoRA easily achieves comparable performance on the fine-tuning dataset in PubMedQA. However, in the case of fine-tuning on MedMCQA, LoRA’s performance is significantly inferior to full fine-tuning in terms of its performance on the fine-tuning dataset. We speculate that fine-tuning on PubMedQA might possess a better low-rank structure, making it easier for LoRA to adapt to the fine-tuning task. On the other hand, MedMCQA is more challenging for LoRA to adapt to, resulting in a larger magnitude of the low-rank matrix and subsequently leading to more significant forgetting.
- L1, L2, and KD penalties have shown the ability to alleviate CF compared to vanilla full fine-tuning. However, they do not consistently match the effectiveness of Wise-ft

In Appendix D, we provide additional results that investigate the impact of early stopping, learning rate, and warm-up strategies on CF.

### 4.3 Discussion with existing works

In this technical report, our primary focus is to conduct extensive experiments on generality forgetting and perform a systematic comparison of existing methods. While we do not claim novelty in our methods or results, we do present some new findings that we believe will contribute to future research in this domain. These findings are briefly discussed as follows:

**VLM part.** We adopt the term “ID and OOD performance” to maintain consistency with previous research, which specifically refers to the performance related to specialty and distribution generality in the previous sections. Previous OOD works have found that fine-tuning VLMs on ImageNet leads to worsened OOD performance and Wise-ft can alleviate this issue [80, 24, 74, 45, 73, 2].

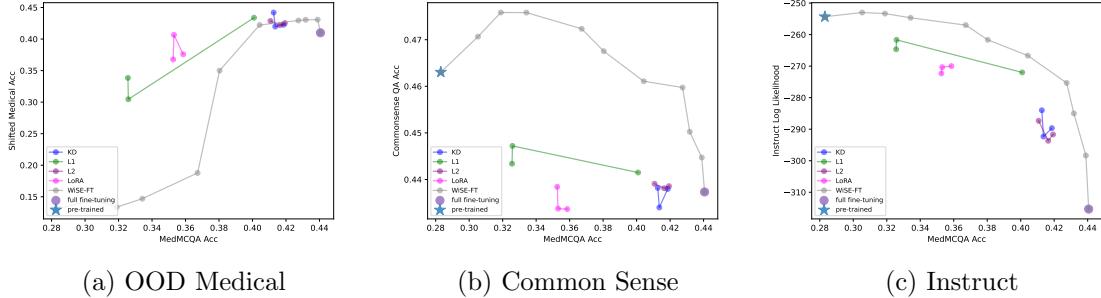


Figure 5: Fine-tune on MedMCQA. We evaluate the forgetting in terms of (a) distribution generality forgetting on the other two medical QA datasets including PubMedQA and MedQA-USMLE, (b) task generality forgetting on common sense tasks including ARC Easy and Challange, Race, and PIQA (c) instruction following tasks including Alpaca, GPT4 instruct and LMFlow.

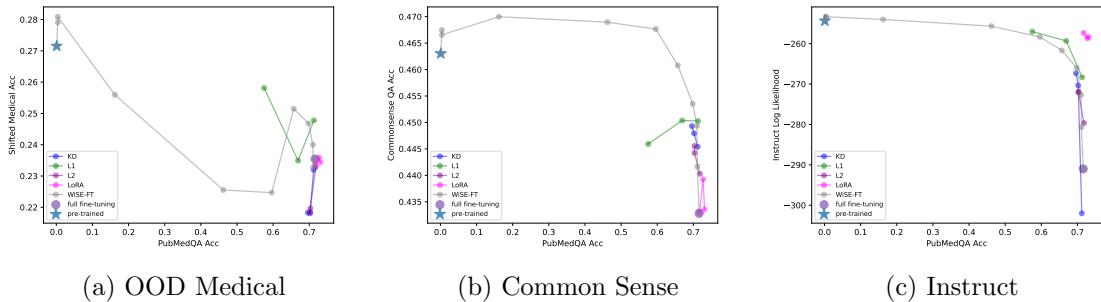


Figure 6: Fine-tune on PubMedQA. We evaluate the forgetting in terms of (a) distribution generality forgetting on the other two medical QA datasets including MedMCQA and MedQA-USMLE, (b) task generality forgetting on common sense tasks including ARC Easy and Challange, Race and PIQA (c) instruction following tasks including Alpaca, GPT4 instruct and LMFlow.

However, existing OOD works haven’t explicitly linked this phenomenon to CF. Specifically, consider a model composed of a featurizer  $\Phi$  and a classifier  $v$  and denote the pre-trained model as  $[\Phi_0, v_0]$ . A line of existing works suggests that the fine-tuned feature encoder  $\Phi$  is as effective as or better than the initial encoder  $\Phi_0$  for the target domain and the drop in OOD performance is attributed to the fine-tuned classifier  $v$  not being suitable for the target domain [65, 58, 36]. However, our results and analysis in Appendix C present a different outcome: we find that  $\Phi$  actually forgets important features for the target domains when compared to  $\Phi_0$ . Additionally, we show that simple methods such as knowledge distillation can achieve comparable performance to Wise-ft, the previous SOTA method.

**LLM part.** Most research on forgetting in natural language processing (NLP) focuses on sequential pre-training [14, 22, 35, 57, 47] and fine-tuning tasks [69, 60, 81, 85, 49]. They either sequentially train a model  $f_\theta$  from scratch on tasks  $[\mathcal{T}_1, \mathcal{T}_2, \dots, \mathcal{T}_K]$  or sequentially fine-tune a pre-trained model

on tasks  $[\mathcal{T}_1, \mathcal{T}_2, \dots, \mathcal{T}_K]$ . Evaluation of forgetting is based on the model’s performance on  $\mathcal{T}_i$  after training it on  $\mathcal{T}_j$ , where  $i < j$ . Our setting differs from theirs as we focus on generality forgetting in  $f_{\theta_0}$  during fine-tuning a single task. We visualize the trade-off between generality and specialty in Figure 5 and 6 when fine-tuning LLM. While such trade-offs have been observed in VLM works [80, 24, 74, 45], we did not find similar results in LLM works. A concurrent study [48] has investigated generality forgetting of LLM during fine-tuning sequences of tasks (see Section A.2 for detailed discussion on the differences in settings), whereas they do not explore methods to alleviate CF. Our results demonstrate that Wise-ft achieves superior performance in mitigating LLM’s catastrophic forgetting, and we observe an intriguing phenomenon where the effectiveness of LoRA in alleviating forgetting depends on the fine-tuning task’s difficulty.

## 5 Conclusion and Limitation

In conclusion, our investigation highlights the delicate trade-off between specialty and generality during the fine-tuning of foundation models. To address this challenge, we explore various regularization methods from continual learning, as well as the weight averaging method (Wise-ft) and parameter-efficient fine-tuning techniques like LoRA. Our findings demonstrate that continual learning and Wise-ft methods effectively alleviate the loss of generality, with Wise-ft outperforming others in achieving a balance between specialty and generality. One limitation is that we haven’t covered the rehearsal methods, which replay a small portion of the pre-trained dataset.

**Limitation.** One notable limitation of our work is that we have not explored the impact of varying model sizes on the forgetting issue and the corresponding methods. We plan to investigate this aspect in future versions.

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## A More Discussions

### A.1 Definition of the task

The definition of a task of VLMs for classification can be found in literature [78], i.e., for two tasks  $\mathcal{T}^i, \mathcal{T}^j$  and  $i \neq j$ , output space is disjoint, i.e.,  $\mathcal{Y}^i \cap \mathcal{Y}^j = \emptyset$ . As for LLMs, the definition is not clearly defined in the literature. In this work, we consider samples  $\mathbf{x}$  from a task sharing the same semantic feature. For example, Medical QA and Common Sense QA are regarded as different tasks since their semantic context is different.

### A.2 Discussion on the settings

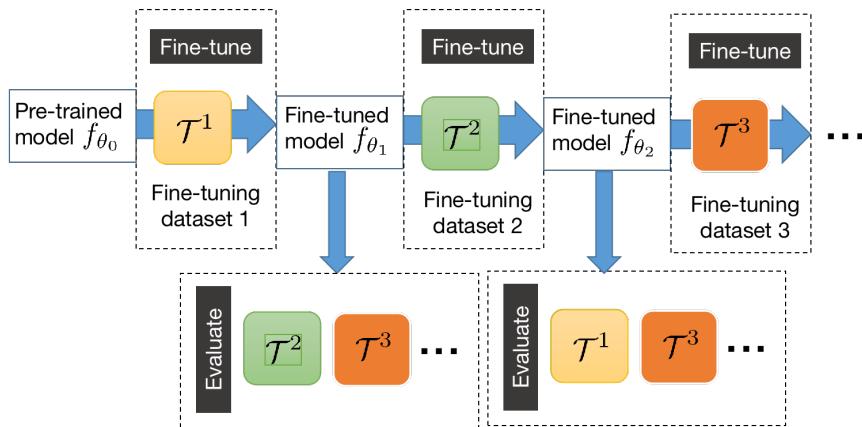


Figure 7: Typical setting on continual learning

Recall that the typical settings in continual learning considers fine-tuning  $f_{\theta_0}$  sequentially on a series of tasks  $[\mathcal{T}^1, \mathcal{T}^2, \mathcal{T}^3 \dots]$  and measure how the fine-tuning on the new task affect the performance of the earlier tasks. For example, how fine-tuning  $f_{\theta}$  on  $\mathcal{T}^3$  leads to the performance drop on task  $\mathcal{T}^1$ . Differently, we only investigate the forgetting around fine-tuning the pre-trained model  $f_{\theta_0}$ . For example, explore the forgetting of  $\{\mathcal{T}^k\}_{k \neq i}$  when fine-tuning  $f_{\theta_0}$  on  $\mathcal{T}^i$ . Similarly,  $\mathcal{T}^i$  can be replaced by another task  $\mathcal{T}^j$  to investigate how fine-tuning  $f_{\theta_0}$  on  $\mathcal{T}^j$  affects the performance of  $\{\mathcal{T}^k\}_{k \neq j}$ . We adopt this new setting because:

- The fine-tuning process typically involves small datasets that can be easily stored in local memory. As an illustration, let's consider the fine-tuning of LLM on a medical task using the MedMCQA dataset for acquiring medical knowledge and the Alpaca dataset for ensuring the LLM's ability to follow human instructions. These datasets are relatively small, with MedMCQA containing 182K samples and Alpaca containing 52K samples. Due to their manageable size, it becomes feasible to obtain and combine these datasets simultaneously for the fine-tuning process. This eliminates the need to perform sequential fine-tuning on each dataset separately. Consequently, the potential impact of sequentially fine-tuning new tasks on the performance of previously fine-tuned tasks becomes less pronounced. However,

preserving the wide-ranging abilities (e.g., common sense and reasoning) of an LLM acquired during pre-training is challenging due to the large size of the pre-training dataset.

- Moreover, recent studies have shown that it is possible to replace the traditional approach of fine-tuning a sequence of tasks by independently fine-tuning each task on  $f_{\theta_0}$  and subsequently combining their weights through interpolation [30, 41, 46]. This weight interpolation approach significantly enhances performance and mitigates catastrophic forgetting compared to conventional methods that sequentially fine-tune one model,  $f_{\theta}$ , on  $[\mathcal{T}^1, \mathcal{T}^2, \mathcal{T}^3 \dots]$ . However, weight interpolation methods still encounter the issue of catastrophic forgetting during fine-tuning  $f_{\theta_0}$  on a single task. This forms the primary research problem addressed in our study.

## B Evaluating the performance of instruction following

Following LMflow [20], we evaluate the performance of instruction by log-likelihood (LL):

$$\begin{aligned} \text{LL} &= \frac{1}{N} \sum_{i=1}^N \log p(\text{sentence}_i | \text{context}_i) \\ &= \frac{1}{N} \sum_{i=1}^N \log p(\text{token}_{i,1}, \text{token}_{i,2}, \dots, \text{token}_{i,n_i} | \text{context}_i), \end{aligned}$$

where  $n_i$  is the length of the token in sentence $_i$ .

## C Verifying the forgetting of fine-tuning CLIP

Specifically, let's consider the fine-tuned CLIP model for classification denoted as  $\theta = [\Phi, v]$ , where  $\Phi$  represents the image feature encoder and  $v$  is the classifier. The results in Figure 4 demonstrate that the model  $[\Phi, v]$  is inferior to the pre-trained model  $[\Phi_0, v_0]$  in terms of OOD performance. However, it is still uncertain whether this discrepancy arises due to CF. For instance, previous works [65, 58, 36] suggest that  $\Phi$  still encodes features as effectively as  $\Phi_0$  and the OOD performance decline since  $v$  is sub-optimal for the target domain.

To isolate the effect of the classifier discussed above, we perform the following experiments to show that the OOD decline is closely related to representation forgetting [17], a common type of CF. Specifically, we store a sequence of checkpoints, namely,  $[\Phi_1, v_1], [\Phi_2, v_2], \dots, [\Phi_t, v_t]$  during fine-tuning on the source domain. We perform linear probing for each checkpoint on the target domain respectively, i.e., obtain

$$\bar{v}_i = \arg \min_v \mathcal{L}_t([\Phi_i, v]),$$

where  $\mathcal{L}_t([\Phi_i, v])$  is the loss on the target domain of  $[\Phi_i, v]$ . Now that we have the  $\bar{v}_i$  which is optimal for the target domain given the featurizer  $\Phi_i$ . We name the accuracy of  $[\Phi_i, \bar{v}_i]$  on the target domain as *probing accuracy*. The probing accuracy  $[\Phi_i, \bar{v}_i]$  measures the effectiveness of the

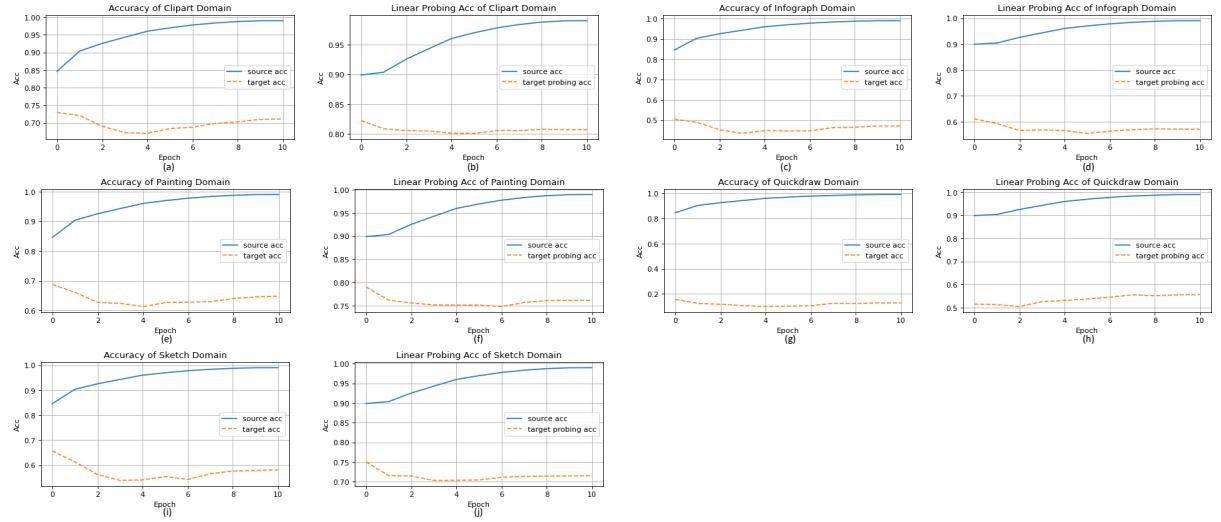


Figure 8: Accuracy and linear probing accuracy of 5 OOD domains in DomainNet.

feature representation by  $\Phi_i$  for the target domain. In Figure 8, we show the trend of accuracy  $[\Phi_i, v_i]$  as well as the probing accuracy  $[\Phi_i, \bar{v}_i]$  on each target domain. In Figure 8, we show that the probing accuracy also drops during fine-tuning, indicating that fine-tuning CLIP indeed suffers from CF.

## D Investigating early stopping, learning rate, and warm-up

In most deep-learning tasks, early stopping becomes an efficient method to prevent overfitting in training. We also test the performance of early stopping in the fine-tuning of large language models. To analyze how the early stopping affects forgetting in large language models, we conduct experiments on different learning rates and different steps of warmup. For each setting, we plot it in three parts, (1) iteration 1-46, every 5 iterations, (2) iteration 100-400, every 50 iterations, (3) iteration 600-1800, every 200 iterations.

As shown in Figure 9 (left), the performance of early stopping for forgetting is sensitive to learning rates. When training with a large learning rate 2e-5, the model has a high accuracy on the MedMCQA dataset while dropping quickly on instruction tasks which indicates an obvious forgetting. With lower learning rates like 1e-6, and 5e-6, the forgetting is significantly alleviated but the in-domain accuracies also become lower.

In addition, we evaluate warm-up to reduce the quick drop at the beginning of fine-tuning with a large learning rate. From the results, warmup can help the catastrophic forgetting at the beginning and achieve high accuracy on the MedMCQA dataset as well. As we vary the warmup steps, we find that it only affects the performance at the beginning of the fine-tuning but not the final results. What's more, all early stopping results including warmup do not give a better method to prevent forgetting than WiSE-FT as shown in Figure 9.

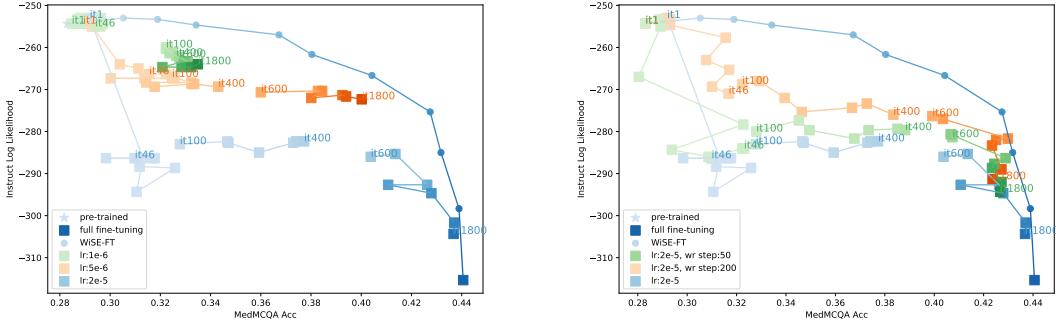


Figure 9: Fine-tune on MedMCQA and test on Instruction task with different learning rates and warmup strategies. left) We show the early stopping results of different learning rates  $1e-6$ ,  $5e-6$ , and  $2e-5$ ; right) We show the early stopping results of different warmup steps 0, 50, and 200 with a learning rate of  $2e-5$ . For both figures, we plot it in three parts, (1) iteration 1-46, every 5 iterations, (2) iteration 100-400, every 50 iterations, (3) iteration 600-1800, every 200 iterations;

## E Experimental Details

Training Dataset	ImageNet	DomainNet('Real')
Optimizer	AdamW	AdamW
Optimizer Hyper-parameter	warmup 500 steps	warmup 500 steps
Learning Rate Schedule	Cosine	Cosine
Warmup	500 Steps	500 steps
Learning Rate	3e-5	3e-5
Epoch	10	10
Steps per epoch	2502	342
Batch Size	512	512

Table 2: Details of fine-tuning CLIP

We use the CLIP model ViT-B/16[59]. We fine-tune the pre-trained model on ImageNet and DomainNet-Real. We use the AdamW optimizer with the default PyTorch settings and choose 512 as batch size. We use a learning rate of  $3 \times 10^{-5}$ , gradient clipping at global norm 1, and fine-tune for a total of 10 epochs. The settings mentioned above are the same with [?].

Training Dataset	PubMedQA	MedMCQA
Optimizer	Adam	Adam
Optimizer Hyper-parameter	(0.9,0.999)	(0.9,0.999)
Max Token Size	512	512
Learning Rate Schedule	liner	linear
Learning Rate	2e-5	2e-5
Epoch	5	5
Steps per epoch	2691	470
Batch Size	14	14

Table 3: Details of fine-tuning Large Language Model

## F Detailed Results

Finetune Methods	Hyper	IN(ImageNet)	IN-V2	IN-R	IN-A	IN-Sketch	ObjectNet	Avg OOD
ZeroShot		68.33	62.00	77.62	49.96	48.26	53.77	58.32
Full Fine-Tune		81.47	70.89	65.34	36.92	45.83	50.18	53.83
WiSE-FT	$\alpha = 0.2$	76.4	68.7	80.1	52.5	57.1	54.2	62.5
	$\alpha = 0.4$	80.5	72.1	79.6	54.1	57.7	53.8	63.5
	$\alpha = 0.6$	82.4	72.9	77.2	53.4	56.2	50.0	61.9
	$\alpha = 0.8$	82.5	72.8	72.7	51.0	53.5	44.6	58.9
l1	$\lambda = 1e - 4$	79.94	71.10	77.23	52.15	51.30	56.12	61.58
	$\lambda = 1e - 5$	81.80	72.26	72.24	46.32	50.26	54.23	59.06
l2	$\lambda = 1e - 0$	71.73	64.35	78.48	50.54	49.34	55.29	59.60
	$\lambda = 1e - 1$	76.88	69.10	78.47	52.68	50.45	56.16	61.37
	$\lambda = 1e - 2$	81.80	71.91	72.22	46.58	50.37	53.89	58.99
	$\lambda = 1e - 3$	81.64	71.54	66.91	38.65	46.89	50.61	54.92
	$\lambda = 1e - 4$	81.50	70.94	65.19	36.57	45.54	50.33	53.71
KD	$\lambda = 5e - 3$	81.49	72.46	78.65	50.43	52.18	56.73	62.09
	$\lambda = 3e - 3$	82.45	73.32	78.5	50.27	52.2	56.92	62.24
	$\lambda = 1e - 3$	83.09	73.57	76.03	46.77	51.05	55.11	60.51
	$\lambda = 3e - 4$	82.52	72.77	70.29	39.16	47.47	51.39	56.22
LoRA	rank=2	75.82	68.13	74.86	49.18	48.15	54.54	58.97
	rank=4	77.00	68.88	73.49	48.37	47.90	54.52	58.63
	rank=8	78.63	69.69	72.57	48.62	48.03	55.01	58.78
	rank=16	79.20	70.12	70.47	45.14	47.34	53.34	57.28
	rank=32	79.63	69.95	69.31	45.37	46.59	53.45	56.93

Table 4: Accuracy(%) results of ImageNet and derived distribution shifts after fine-tuning CLIP ViT-B/16 on ImageNet.

Finetune Methods	Hyper	Real	Clipart	Infograph	Painting	Quickdraw	sketch	Avg OOD
ZeroShot		84.59	72.93	50.55	68.71	15.68	65.69	54.71
Full Fine-Tune		99.0	71.07	47.15	64.78	12.9	58.12	50.8
WiSE-FT	$\alpha = 0.2$	90.2	75.47	52.91	70.83	16.97	67.31	56.7
	$\alpha = 0.4$	94.36	76.22	53.56	71.05	17.16	67.0	57.0
	$\alpha = 0.6$	97.27	75.69	52.67	69.9	16.35	65.36	55.99
	$\alpha = 0.8$	98.65	73.99	50.54	67.85	14.87	62.37	53.93
l1	$\lambda = 1e - 3$	90.6	74.71	52.64	69.05	14.66	65.14	55.24
	$\lambda = 1e - 4$	93.4	75.19	52.0	68.61	14.92	64.58	55.06
	$\lambda = 1e - 5$	93.4	75.19	52.0	68.61	14.92	64.58	55.06
	$\lambda = 1e - 6$	99.08	71.8	48.32	65.83	13.52	59.54	51.8
l2	$\lambda = 1e - 0$	89.96	73.61	52.77	68.56	14.14	64.85	54.79
	$\lambda = 1e - 1$	91.3	75.07	52.81	69.21	14.9	65.24	55.45
	$\lambda = 1e - 2$	91.3	75.07	52.81	69.21	14.9	65.24	55.45
	$\lambda = 1e - 3$	99.05	71.9	48.07	65.45	12.42	59.85	51.54
KD	$\lambda = 1e - 2$	95.14	75.39	52.15	69.73	15.49	66.01	55.75
	$\lambda = 1e - 3$	98.89	75.46	51.8	69.23	14.65	64.9	55.21
	$\lambda = 1e - 4$	99.14	71.59	47.06	64.66	12.65	59.11	51.01
	$\lambda = 1e - 5$	99.02	69.56	44.63	63.33	12.65	56.86	49.41
LoRA	rank=16	96.05	69.94	46.02	64.26	12.64	58.29	50.23

Table 5: Accuracy(%) results of DomainNet-real and other domains of DomainNet after fine-tuning CLIP ViT-B/16 on DomainNet-Real.

Finetune Methods		Hyperparameters	MedMCQA	PubMedQA	MedQA-USMLE	Avg OOD Medical
base			28.31	0.10	26.00	13.05
full fine-tune			44.06	41.60	40.38	40.99
wise	$\alpha = 0.2$		43.17	46.20	39.91	43.05
	$\alpha = 0.4$		40.43	48.00	36.45	42.22
	$\alpha = 0.6$		36.72	9.90	27.65	18.78
	$\alpha = 0.8$		31.89	1.50	25.22	13.36
l1	$\lambda = 1e - 4$		32.58	32.70	28.20	30.45
	$\lambda = 1e - 5$		32.56	41.30	26.39	33.85
	$\lambda = 1e - 6$		40.09	50.70	36.06	43.38
l2	$\lambda = 1e - 4$		41.07	47.40	38.33	42.87%
	$\lambda = 1e - 5$		41.64	45.90	38.49	42.20
	$\lambda = 1e - 6$		41.93	46.40	38.65	42.52
kd	$\lambda = 1e - 4$		41.26	50.70	37.71	44.20%
	$\lambda = 1e - 5$		41.86	45.90	38.65	42.27
	$\lambda = 1e - 6$		41.36	45.30	38.65	41.97
lora	rank=4		35.26	42.90	30.64	36.77
	rank=8		35.31	51.00	30.32	40.66
	rank = 16		35.86	42.80	32.36	37.58

Table 6: Accuracy(%) results of the medical QA datasets after fine-tuning Galactica on MedMCQA.

Finetune Methods	Hyperparameters	ARC Easy	ARC Challenge	Race	PIQA	Avg CommonSense QA
base		62.42/58.63	27.90/30.80	31.67	63.22/63.60	46.30
full fine-tune		54.63/48.61	29.18/31.57	29.86	61.26/61.10	43.73
wise	$\alpha = 0.2$	57.58/52.61	30.46/33.53	29.76	62.30/63.22	45.02
	$\alpha = 0.4$	60.52/56.10	29.86/33.79	30.72	63.33/63.44	46.11
	$\alpha = 0.6$	62.63/58.88	31.14/33.87	31.67	63.49/64.15	47.23
	$\alpha = 0.8$	63.68/59.85	30.20/32.08	32.63	63.82/63.76	47.58
l1	$\lambda = 1e - 4$	59.60/55.68	27.30/32.00	28.71	63.28/63.06	44.72
	$\lambda = 1e - 5$	58.75/54.63	27.56/30.72	27.66	63.38/62.30	44.34
	$\lambda = 1e - 6$	57.11/52.61	29.44/31.91	27.75	62.30/62.40	44.15
l2	$\lambda = 1e - 4$	56.52/50.34	28.58/31.74	29.00	61.53/61.48	43.91
	$\lambda = 1e - 5$	55.56/50.29	28.33/31.23	30.05	61.32/61.48	43.81
	$\lambda = 1e - 6$	55.93/49.62	28.50/30.72	29.19	61.81/61.48	43.86
kd	$\lambda = 1e - 4$	57.24/51.64	27.30/29.44	29.47	61.26/62.19	43.82
	$\lambda = 1e - 5$	56.86/50.21	27.65/30.38	29.47	61.21/61.32	43.80
	$\lambda = 1e - 6$	55.68/49.75	27.90/31.06	29.19	60.83/61.32	43.40
lora	rank=4	56.23/50.29	27.39/30.29	29.19	62.57/61.70	43.84
	rank=8	54.46/47.81	27.13/30.63	29.28	62.62/61.10	43.37
	rank=16	55.47/48.27	27.22/30.89	28.04	62.73/60.99	43.36

Table 7: Accuracy(%) / Normed Accuracy(%) results of the common sense QA datasets after fine-tuning Galactica on MedMCQA. We also give the normed accuracy at the right if there are different numbers of choices in questions.

Finetune Methods	Hyperparameters	LMFlow EN	LMFlow CN	Alpaca	GPT4 EN	GPT4 CN	Avg EN Instruction
base		248	913	207	308	848	254.33
full fine-tune		306	1044	258	382	968	315.33
wise	$\alpha = 0.2$	276	985	235	344	916	285.00
	$\alpha = 0.4$	258	948	220	322	880	266.67
	$\alpha = 0.6$	249	925	212	310	860	257.00
	$\alpha = 0.8$	246	913	208	306	848	253.33
l1	$\lambda = 1e - 4$	254	929	215	316	864	261.67
	$\lambda = 1e - 5$	258	933	216	320	868	264.67
	$\lambda = 1e - 6$	266	957	222	328	888	272.00
l2	$\lambda = 1e - 4$	280	991	234	348	920	287.33
	$\lambda = 1e - 5$	286	1006	239	356	932	293.67
	$\lambda = 1e - 6$	284	1007	239	352	932	291.67
kd	$\lambda = 1e - 4$	276	989	232	344	916	284.00
	$\lambda = 1e - 5$	282	1004	237	350	932	289.67
	$\lambda = 1e - 6$	286	1006	239	352	932	292.33
lora	rank=4	266	957	223	328	888	272.33
	rank=8	264	954	223	324	884	270.33
	rank=16	264	953	222	324	884	270.00

Table 8: Negative Log Likelihood (NLL) of the instruction following dataset after fine-tuning Galactica on MedMCQA.

Fine-tune Methods	Hyperparameters	PubMedQA	MedMCQA	MedQA-USMLE	Avg OOD Medical
base		0.10	28.31	26.00	27.15
full		71.60	23.52	23.57	23.55
wise	$\alpha = 0.2$	71.00	22.23	25.77	24.00
	$\alpha = 0.4$	65.70	23.12	27.18	25.15
	$\alpha = 0.6$	46.20	23.98	21.13	22.55
	$\alpha = 0.8$	0.40	28.71	27.10	27.91
l1	$\lambda = 1e - 4$	71.30	24.81	24.74	24.78
	$\lambda = 1e - 5$	57.50	24.29	27.34	25.81
	$\lambda = 1e - 6$	66.90	24.60	22.39	23.49
l2	$\lambda = 1e - 4$	71.80	23.33	23.25	23.29
	$\lambda = 1e - 5$	70.30	21.78	21.92	21.85
	$\lambda = 1e - 6$	70.30	22.02	21.92	21.97
kd	$\lambda = 1e - 4$	71.20	22.52	23.88	23.20
	$\lambda = 1e - 5$	69.60	21.59	22.07	21.83
	$\lambda = 1e - 6$	70.20	21.78	21.84	21.81
lora	rank=4	73.10	21.42	25.45	23.44
	rank=8	72.70	21.87	25.29	23.58
	rank=16	71.70	23.48	23.25	23.36

Table 9: Accuracy(%) results of the medical QA datasets after fine-tuning Galactica on PubMedQA.

Fine-tune Methods	Hyperparameters	ARC Easy	ARC Challenge	Race	PIQA	Avg CommonSense QA
base		62.42/58.63	27.90/30.80	31.67	63.22/63.60	46.30
full		53.49/47.69	26.96/30.63	30.43	62.24/61.97	43.28
wise	$\alpha = 0.2$	58.04/52.27	27.65/30.72	31.39	62.68/62.89	44.94
	$\alpha = 0.4$	60.48/55.93	28.41/31.57	31.77	63.66/64.20	46.08
	$\alpha = 0.6$	62.12/58.12	28.33/32.25	32.82	64.31/64.69	46.90
	$\alpha = 0.8$	62.71/59.72	28.58/31.48	32.15	63.55/64.85	46.75
l1	$\lambda = 1e - 4$	57.41/54.04	26.45/29.01	32.54	63.71/62.30	45.03
	$\lambda = 1e - 5$	58.29/54.12	26.19/29.44	30.72	63.17/62.30	44.59
	$\lambda = 1e - 6$	58.71/54.63	26.71/30.55	30.91	63.82/63.06	45.04
l2	$\lambda = 1e - 4$	56.65/51.18	26.71/31.23	30.14	62.62/60.61	44.03
	$\lambda = 1e - 5$	57.37/52.82	26.96/29.78	31.10	62.79/62.35	44.55
	$\lambda = 1e - 6$	56.82/52.27	27.05/29.27	30.72	63.11/62.19	44.42
kd	$\lambda = 1e - 4$	57.87/51.81	26.79/29.78	31.58	61.92/60.28	44.54
	$\lambda = 1e - 5$	57.66/53.49	27.39/29.44	31.67	63.00/62.13	44.93
	$\lambda = 1e - 6$	56.82/52.10	27.13/28.41	31.67	63.55/62.19	44.79
lora	rank=4	55.93/51.09	24.83/29.69	30.14	62.51/61.26	43.36
	rank=8	55.85/51.26	26.54/30.29	30.53	62.79/61.43	43.92
	rank=16	56.06/51.60	25.00/29.61	30.05	62.13/61.53	43.31

Table 10: Accuracy(%) / Normed Accuracy(%) results of the common sense QA datasets after fine-tuning Galactica on PubMedQA. We also give the normed accuracy at the right if there are different numbers of choices in questions.

Fine-tune Methods	Hyperparameters	LMFlow EN	LMFlow CN	Alpaca	GPT4 EN	GPT4 CN	Avg EN Instruction
base		248	913	207	308	848	254.33
full		284	1122	239	350	1024	291.00
wise	$\alpha = 0.2$	264	1030	226	328	948	272.67
	$\alpha = 0.4$	253	974	216	316	904	261.67
	$\alpha = 0.6$	248	939	211	308	872	255.67
	$\alpha = 0.8$	246	919	208	306	852	253.33
l1	$\lambda = 1e - 4$	262	972	215	328	900	268.33
	$\lambda = 1e - 5$	250	922	209	312	856	257.00
	$\lambda = 1e - 6$	252	923	210	316	856	259.33
l2	$\lambda = 1e - 4$	272	1086	229	338	968	279.67
	$\lambda = 1e - 5$	266	963	220	330	888	272.00
	$\lambda = 1e - 6$	266	963	220	330	888	272.00
kd	$\lambda = 1e - 4$	294	1270	246	366	1112	302.00
	$\lambda = 1e - 5$	260	960	218	324	884	267.33
	$\lambda = 1e - 6$	264	963	219	328	888	270.33
lora	rank=4	251	924	212	312	856	258.33
	rank=8	251	931	213	312	860	258.67
	rank=16	250	929	212	310	860	257.33

Table 11: Negative Log Likelihood (NLL) of the instruction following datasets after fine-tuning Galactica on PubMedQA.