Model-Agnostic Multitask Fine-tuning for Few-shot Vision-Language Transfer Learning

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Abstract
Despite achieving state-of-the-art zero-shot performance, existing vision-language models, e.g., CLIP, still fall short of domain-specific classification tasks, e.g., Fungi Classification. In the context of few-shot transfer learning, traditional fine-tuning fails to prevent highly expressive model from exploiting spurious correlations in the training data. On the other hand, although model-agnostic meta-learning (MAML) presents as a natural alternative for transfer learning, the expensive computation due to implicit second-order optimization limits its use in large-scale models and datasets. In this work we aim to further improve the generalization of existing vision-language models on unseen tasks via a simple yet efficient fine-tuning strategy based on uniform task sampling. We term our method as Model-Agnostic Multitask Fine-tuning (MAMF). Compared with MAML, MAMF discards the bi-level optimization and uses only first-order gradients, which makes it easily scalable and computationally efficient. Due to the uniform task sampling procedure, MAMF consistently outperforms the classical fine-tuning method for few-shot transfer learning on five benchmark datasets. Empirically, we further discover that the effectiveness of first-order MAML is highly dependent on the zero-shot performance of the pre-trained model, and our simple algorithm can outperform first-order MAML on more challenging datasets with low zero-shot performance. Code and processed data are publicly available for research purposes at https://github.com/MikeWangWZHL/Multitask-Finetuning-CLIP.

1 Introduction
While existing machine learning models have achieved human-level performance at various individual tasks, they generally lack the ability of fast adaptation and generalization. In recent years, transfer learning has been proven to be effective on a wide range of Computer Vision [He et al., 2016; dosovitskiy et al., 2020] and Natural Language Processing [Devlin et al., 2019; Lewis et al., 2020] tasks. Specifically, recent advances in large-scale vision-language models such as CLIP [Radford et al., 2021] and ALIGN [Jia et al., 2021] using contrastive pretraining have demonstrated strong zero-shot transfer ability on a wide range of classification tasks. However, these models still have certain limitations on concepts that require reasoning or extensive domain knowledge, such as Object Counting and Fungi Classification. In the traditional pretraining-fine-tuning paradigm, training and testing data are drawn from the same distribution. This is not sufficient to evaluate whether a model has truly learned a new concept, in the sense that modern deep neural networks can easily exploit spurious correlations in the training distribution. Thus, we first propose a new evaluation scheme for few-shot transfer learning in which we replace the original testing phase with meta-testing (Section 3). The goal is to find an efficient fine-tuning algorithm that can make a pre-trained model learn new concepts with few examples. To this end, one potential approach is model-agnostic meta-learning (MAML) [Finn et al., 2017], which has been well-studied in few-shot learning settings but is rarely applied to end-to-end fine-tuning on large pretrained models. To improve the computational efficiency of MAML, prior work has proposed various first-order variants [Finn et al., 2017; Raghu et al., 2019; Rajeswaran et al., 2019; Nichol et al., 2018] of the original MAML. They all achieved comparable performance despite the fact that they are using different optimization algorithms. This observation motivates us to ask the following question: If the specific choice of optimization method is not the key in the empirical success of MAML, what would be?

We conjecture that uniform task sampling is an essential ingredient in learning new concepts efficiently. To verify this hypothesis, we propose a simple fine-tuning algorithm, Model-Agnostic Multitask Fine-tuning (MAMF), which simplifies MAML by using only first-order gradient-based optimization while keeping the uniform task sampling procedure. We perform comprehensive experiments in a few-shot vision-language transfer learning setting using a contrastive classification framework following [Radford et al., 2021]. We compare our algorithm with classical fine-tuning, which does not perform uniform task sampling, and first-order MAML (FOMAML) [Finn et al., 2017], which uses more complex bi-level optimization upon sampled tasks. Like MAML, our al-
algorithms is model-agnostic and is not confined to classification tasks. The main contributions of this paper are as follows:

- We demonstrate that uniform task sampling is the key to fast adaptation and generalization in few-shot transfer learning.
- We propose a simple yet effective fine-tuning algorithm, Model-Agnostic Multitask Fine-tuning, that consistently outperforms classic fine-tuning and outperforms FOMAML on more challenging tasks.
- We investigate using MAML for fine-tuning and discover that the effectiveness of FOMAML is highly dependent on the zero-shot performance of the pretrained model.

2 Related Work

Model-Agnostic Meta-Learning (MAML) The idea of MAML [Finn et al., 2017] is to find a good initialization point of the network parameters that can quickly adapt to new tasks with a few examples. Instead of doing empirical risk minimization (ERM) as in classical fine-tuning, MAML focuses on doing optimization for generalization. MAML uses meta-testing, where it splits the test set into support and query sets, and the model is further updated on the support set and evaluated on the query set. The original MAML uses a bi-level optimization scheme and requires computing the second-order derivatives, which is computationally expensive and memory consuming. Several recent works [Nichol et al., 2018; Raghu et al., 2020; Rajeswaran et al., 2019] focused on improving MAML’s optimization strategy and demonstrated comparable performance. However, the role of task sampling in the empirical success of MAML remains unclear. In this work, we show that the uniform task sampling procedure itself is crucial for few-shot transfer learning.

The Effectiveness of MAML Another line of work attempts to address an open question of MAML: Why MAML works in some cases but not others? One shared message conveyed by previous attempts is that MAML may not be very different from empirical risk minimization (ERM) (also known as joint training [Finn et al., 2019]). Specifically, in the view of sample complexity, [Gao and Sener, 2020] showed that MAML is only effective when the sample complexity is low and the sample size budget is high. In the view of optimization, [Collins et al., 2020] showed that MAML outperforms ERM when the tasks are either hard or easy. [Wang et al., 2021] shows that the optimization objective of MAML is equivalent to that of multitask learning, and they converge to the same hypothesis when the network is deep and wide. However, little work is done on exploring the effectiveness of MAML for fine-tuning. In this work, we investigate using MAML for few-shot transfer learning based on a large-scale pretrained vision-language model. We show that original MAML is inapplicable for fine-tuning large neural networks, e.g., CLIP, and the effectiveness of FOMAML is highly dependent on the zero-shot performance of the pretrained model.

Fine-tuning methods Fine-tuning large-scale pretrained models, either by learning a new linear classifier [Kornblith et al., 2019] or by end-to-end tuning [Devlin et al., 2019], has been a well-established paradigm for various machine learning problems. However, as raised by [Brown et al., 2020], with increasing expressiveness of modern neural networks, traditional fine-tuning fails to prevent the model from exploiting spurious correlations in the relatively small training data. Recent work on fine-tuning CLIP [Wortsman et al., 2021] started to focus on maintaining out-of-distribution robustness instead of solely evaluating on in-distribution performance. Inspired by MAML, we propose incorporating meta-testing into few-shot transfer learning evaluation, which serves as another attempt to mitigate the inherent limitation of traditional fine-tuning.

3 Problem Formulation

We are interested in a few-shot transfer learning problem where we have a pretrained model $\theta$ with initial parameters $\theta$. Let $\tau^{tr}$ be a training task sampled from a distribution $p(\tau^{tr})$ over tasks, and $\tau^{ts}$ be a testing task sampled from $p(\tau^{ts})$, where in our context a task is defined to an induced classification problem by restricting the output space from the original problem (see Figure 1 for illustration). The objective is to find an updated model parameter $\tilde{\theta}$ that minimizes the expected loss on all testing tasks $\mathbb{E}_{\tau^{ts} \sim p(\tau^{ts})} \left[ L_{\tau^{ts}}(\tilde{\theta}) \right]$ where $L_{\tau^{ts}}$ denotes the loss corresponding to testing task $\tau^{ts}$. Specifically, for a classification problem with $M$ classes in total, we define a task as a subset of $N$ classes randomly sampled from the $M$ classes. We further denote $N^{tr},N^{ts}$ as the number of classes in each task and $T^{tr},T^{ts}$ as the total number of sampled tasks in training and testing respectively.

Traditional Fine-tuning Setting Take Figure 1 (a) as an example. In a traditional fine-tuning setting, we have $T^{tr} = 1$ training tasks with $N^{tr} = M$ classes, and $T^{ts} = 1$ testing tasks with $N^{ts} = M$ classes. That is, both training and testing sets are treated as one single task containing data points from all $M$ classes.

Meta-testing Meta-testing is first introduced by related work in meta-learning [Thrun and Pratt, 2012; Vinyals et al., 2016; Finn et al., 2017]. As shown in the testing phase of Figure 1 (b,c,d), in contrast to traditional fine-tuning, we first sample $T^{ts}$ tasks ($T^{ts} > 1$), each containing data points from $N^{ts}$ classes ($1 < N^{ts} < M$). For each sampled testing task $\tau^{ts}$, we further randomly split the data points into two disjoint sets, i.e., support set $A$ and query set $B$, with corresponding loss $L_{\tau^{ts},A}$ and $L_{\tau^{ts},B}$. Then we further update the model parameters on the support set and evaluate on the query set.

4 Reformulating Traditional Fine-tuning using Meta-testing

Our goal is to enable and evaluate a pretrained model’s capability of generalizing to new concepts with few examples. As mentioned in the introduction, the traditional fine-tuning setting is not sufficient since the training and testing data points are drawn from the same distribution. Therefore, we propose to replace the original joint testing in traditional fine-tuning with meta-testing. As described in detail in Section 3, by
uniformly sampling multiple tasks during meta-testing, we can distinguish the testing distribution from training, which largely prevents the model from exploiting spurious correlations in the training set. Essentially, we make the original problem more challenging by requiring the model to quickly generalize to potentially unseen tasks during testing. In the following Sections 4.1, 4.2, we give the objective functions of Classical Fine-tuning and MAML Fine-tuning in our reformulated setting.

4.1 Classical Fine-tuning with Meta-testing

To minimize the expected loss on all testing tasks, we first consider the Classical Fine-tuning method in which \( N = M, T^{tr} = 1 \). Namely we treat the entire training set as one single task and train the model to minimize the expected loss over all training samples:

\[
\min_{\theta} \mathbb{E}_{\tau^{ts} \sim p(\tau^{ts})} \left[ \mathcal{L}_{\tau^{ts}, B} \left( U^{tr}_{\tau^{ts}, A}(\theta) \right) \right], \quad \bar{\theta} = U^{tr}_{\tau^{ts}}(\theta)
\]

where \( U^{tr}_{\tau^{ts}, A} \) is the optimization procedure that updates the initial pretrained parameter \( \theta \) using data from training task \( \tau^{ts}_1 \), here \( \tau^{ts}_1 \) corresponds to the entire training set. \( U^{tr}_{\tau^{ts}, A} \) is the optimization procedure that further updates the updated parameter \( \bar{\theta} \) from the training phase on the support set of a testing task \( \tau^{ts} \).

4.2 MAML Fine-tuning with Meta-testing

We investigate using MAML for fine-tuning with meta-testing. In MAML, we also sample tasks during training, mimicking the meta-testing phase. For each training task \( \tau^{tr} \), we further split the data points into support and query sets, and then perform bi-level optimization. The objective of MAML in the context of transfer learning can be written as follows:

\[
\min_{\theta} \mathbb{E}_{\tau^{ts} \sim p(\tau^{ts})} \left[ \mathcal{L}_{\tau^{ts}, B} \left( U^{tr}_{\tau^{ts}, A}(\theta) \right) \right], \quad \bar{\theta} = \min_{\theta} \mathbb{E}_{\tau^{ts} \sim p(\tau^{ts})} \left[ \mathcal{L}_{\tau^{ts}, B} \left( U^{tr}_{\tau^{ts}, A}(\theta) \right) \right]
\]

where \( U^{tr}_{\tau^{ts}, A}(\theta) \) is the optimization procedure that updates the initial parameter \( \theta \) for one or more steps on the support set of a training task \( \tau^{tr} \).

5 Model-Agnostic Multitask Fine-tuning

Previous MAML-like methods update model parameters iteratively via a complex bi-level optimization scheme [Finn et al., 2017; Raghu et al., 2020; Rajeswaran et al., 2019], which is computationally expensive and only achieved limited improvements against simple ERM in some cases. Inspired by related work in the area of multitask learning [Maurer et al., 2016; Tripuraneni et al., 2020] that demonstrates the effect of task sampling in the generalization bounds for transfer learning problems, we hypothesize that the uniform task sampling process itself is more important than specific choice of optimization method. To verify this hypothesis, we propose a simple fine-tuning algorithm, Model-Agnostic Multitask Fine-tuning (MAMF), in which we also sample multiple tasks on the training set, but then we perform simple first-order gradient-based optimization on each task sequentially, without further splitting the tasks into support and query sets. Note that the randomly sampled tasks during training are independent from testing. The objective of MAMF can be written as:

\[
\min_{\theta} \mathbb{E}_{\tau^{ts} \sim p(\tau^{ts})} \left[ \mathcal{L}_{\tau^{ts}, B} \left( U^{tr}_{\tau^{ts}, A}(\theta) \right) \right], \quad \bar{\theta} = \theta_{i}, \quad i = T^{tr}
\]

where \( \theta_{i} = U^{tr}_{\tau^{ts}}(\theta_{i-1}), \quad i \in \{1, 2, \ldots, T^{tr}\}, \quad \theta_{0} = \theta \). And \( U^{tr}_{\tau^{ts}} \) is the optimization procedure that updates the parameters from the previous task on the current training task \( \tau^{ts}_i \). Figure 1 depicts a comparison of different data sampling and optimization schemes in different algorithms. The detailed MAMF algorithm is shown in Algorithm 1. Note that MAMF is closely related to Reptile [Nichol et al., 2018]. The major difference is that here we further simplify the updating rule of \( \theta \) by eliminating the hyper-parameter of step size, and we start with pretrained model parameters. Compared
with the bi-level optimization scheme in MAML, our algorithm is computationally simple, which requires only first-order gradient-based optimization methods such as stochastic gradient descent (SGD).

6 Experiment

6.1 Evaluation Benchmarks

In this work, we compare the few-shot transfer performance on five datasets representing various concepts: Clevr-Counting [Johnson et al., 2017], Amazon Berkeley Objects (ABO) [Collins et al., 2021] Material, Fungi [Su et al., 2021], Mini-Imagenet [Vinyals et al., 2016], Caltech-UCSD Birds 200 (CUB) [Welinder et al., 2010]. We further randomly split each dataset into disjoint training, development, and test sets, and perform subsampling to frame the experiments in a few-shot setting. Specifically, for ABO Material, we construct a subset of the original dataset by clustering images according to their Material attribute. We then manually filter out noisy samples that have multiple major materials. Table 1 shows the statistics of each dataset.

| Dataset         | M  | S_{tr} | S_{ts}^A | S_{ts}^B |
|-----------------|----|--------|----------|----------|
| ClevrCounting   | 10 | 60     | 10       | 10       |
| Fungi           | 20 | 60     | 10       | 10       |
| ABO Material    | 9  | 50     | 15       | 15       |
| Mini Imagenet   | 10 | 60     | 10       | 10       |
| CUB             | 10 | 60     | 10       | 10       |

Table 1: Dataset statistics. M is the total number of classes; $S_{tr}$ is the number of training samples per class; $S_{ts}^A$ and $S_{ts}^B$ are the number of support set and query set samples per class during meta-testing respectively.

6.2 Contrastive Classification Framework

We compare three algorithms (Classical Fine-tuning, MAML Fine-tuning, and MAMF) using an identical state-of-the-art pretrained model CLIP [Radford et al., 2021]. We create text inputs using templates filled with label names. A full list of templates we use for each task can be found in Appendix A. Table 1. Figure 2 shows an example task from the Clevr-Counting dataset, where we use a text input such as “An image with 2 objects” with “2” as the label name. We use the contrastive classification framework following [Radford et al., 2021] to compute the dot product of <image, text> representations and select the label that has the highest score. Any off-the-shelf image encoder and text encoder can be plug-in to this framework.

6.3 Experimental Setup

We aim to investigate two main questions experimentally:

- **Q1**: Is uniform task sampling during training beneficial to few-shot transfer learning?
- **Q2**: Is the bi-level optimization in MAML effective for few-shot transfer learning?

To answer the first question, we compare MAMF with Classical Fine-tuning; for the second question, we explore using MAML for fine-tuning CLIP. To apply MAML on large-scale models, such as CLIP, we adopt FOMAML, a first-order variant of MAML, since the original second-order variant is inapplicable due to large memory requirements. Implementation details are provided in Appendix A.

For a given dataset with $M$ classes in total, we experiment with various task configurations regarding the number of subsampled classes $N_{ts}$, where $2 \leq N_{ts} \leq M$. That is, during meta-testing, each task can be formulated as a $N_{ts}$-way classification and we randomly sample $T_{ts}$ such tasks. During training, for Classical Fine-tuning, we have training task configuration as $N_{tr} = M, T_{tr} = 1$; for MAMF and FOMAML, we set $N_{tr} = N_{ts} = N, T_{tr} = T_{ts} = T$. To ensure that all classes have a high probability of being sampled during training and testing, we determine $T$ based on $N$, i.e., $T = \frac{\log(0.001)}{\log(1 - \frac{1}{N})}$. That is, with probability higher than 0.999, we are able to cover all classes if $T$ tasks are being sampled.

Within each task, we uniformly sample mini-batches across all data points. We use cross-entropy loss for both training $\mathcal{L}_{tr}$ and meta-testing $\mathcal{L}_{ts}$ for all algorithms. As shown in Figure 3, for each choice of $N$, we repeat the experiment five times with different random seeds and report the average accuracy across all five runs on both development and production servers.

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1In our preliminary experiments, original MAML fails on one Tesla V100 GPU with 16GB DRAM due to cuda out-of-memory.
6.4 Results

Answer to Q1: Uniform task sampling is important. Comparing the performance of MAMF (red line) and Classical Fine-tuning (yellow line), our MAMF algorithm consistently outperforms Classical Fine-tuning on all five datasets. Recall that the only difference between MAMF and Classical Fine-tuning is whether we perform uniform task sampling during training. This empirical result shows that uniform task sampling itself serves as an important procedure for learning new concepts in a few-shot setting. We further do ablation study by decreasing the number of training tasks \( T \) for a fixed \( N = 5 \) on CleVRCounting dataset. Figure 4 shows that when the number of training tasks increases, MAMF consistently achieves better performance and starts to outperform other algorithms. Furthermore, based on simple statistics, given \( T = 5 \), the probability for the sampled tasks to cover the whole training set is already larger than 95%. However, for \( T \geq 5 \), we can still see an increasing trend in the performance of MAMF, which indicates the benefit of uniform task sampling.

Answer to Q2: MAML is not effective on learning initially challenging concepts compared with our MAMF.

Our study focuses on the concepts that have a low zero-shot performance, since one critical challenge for few-shot transfer learning is understanding concepts that perform poorly without examples. Interestingly, we observe a visible correlation between the effectiveness of FOMAML and the zero-shot performance. The pattern is, whenever zero-shot performance is low, FOMAML tends to be less effective. For example, on CUB (Figure 3 c) where the zero-shot accuracy ranges from 0.5 to 0.8, FOMAML outperforms other algorithms in most cases. However, on CleVRCounting (Figure 3 a) where the zero-shot accuracy ranges from 0.3 to 0.75, both MAMF and Classical Fine-tuning consistently outperform FOMAML.

To further visualize this correlation, we plot a Winner Map (Figure 5) which depicts the “winner” method for each task configuration on all development and test sets. The x-axis is the zero-shot CLIP performance. Each dot represents a task configuration in Figure 3. We can see a clear pattern showing that MAMF outperforms other algorithms when the task is initially more challenging, i.e., the zero-shot performance is lower. As the zero-shot accuracy increases, FOMAML (green dots) is more likely to dominate.

To better understand why MAMF outperforms FOMAML on datasets such as CleVRCounting, we examine the image embedding resulted from different algorithms using t-SNE\(^2\) [Van der Maaten and Hinton, 2008]. As shown in Figure 6, we can see that compared with image embedding from FOMAML, the class clusters from MAMF have lower intra-class to inter-class variance ratio, that is the classes are more separate from each other and more tightly clustered.

Based on the aforementioned observation, we conclude that FOMAML is highly sensitive to the performance of the pretrained model and is less effective when the task is inherently more challenging, e.g., Counting. However, it is particularly useful when the model already has a good initialization for a given task. On the other hand, MAMF is more robust to the zero-shot performance, and can outperform FOMAML on initially harder tasks. Recall that the main difference between MAMF and FOMAML is that MAMF does not use bi-level optimization.

6.5 Discussion

In this section, we give theoretical reasoning on why uniform task sampling is important and why the effectiveness of MAML depends largely on zero-shot performance.

In the literature of multitask learning, [Maurer et al., 2016] showed that the excess risk, namely the difference between the learned parameters and the optimal ones, scales as \( O(1/\sqrt{T}) + O(1/\sqrt{n}) \), where \( t \) is the number of tasks and \( n \) is the number of training data per task. [Tri puraneni et al., 2020] further integrated task diversity into the generalization bound showing that the transfer learning risk decays with increasing number of training tasks as well as task diversity. Here, the task diversity is defined to encode how well the training tasks can cover the space captured by the learned representation needed for predicting on new tasks. In our multi-task formulation (Section 3), the Classical fine-tuning is essentially sampling only one task which is identical to the whole training set. Although it contains all the training signals as MAMF, the task diversity is lower in the sense that the learned representation is narrowly fit to this one task, making it hard to generalize to new tasks during meta-testing.

In order to investigate the relationship between MAML and Empirical Risk Minimization (ERM), [Gao and Sener, 2020] provided sample complexity bounds for ERM and MAML. Here, sample complexity is represented as the sum of Euclidean norm of the gradients from ERM and MAML after \( k_{tr} \) iterations of training and \( k_{ts} \) iterations of meta-testing. The bounds for ERM and MAML can be written as \( O(\sqrt{\Lambda + \Lambda^\text{erm}})(C_{tr}^\text{erm}k_{tr} + C_{ts}k_{ts}) \) and \( O(C_0k_{tr} + \sqrt{\Lambda + \Lambda^\text{maml}})(C_{tr}^\text{maml}k_{tr} + C_{ts}k_{ts}) \) respectively, where \( C_0, C_{tr}^\text{erm}, C_{tr}^\text{maml}, C_{ts} \) are non-negative constants from reasonable assumptions on the risk function and the optimization method. The main observation from [Gao and Sener, 2020] is that \( C_{tr}^\text{erm} > C_{tr}^\text{maml} \), that is, ERM results in a tighter bound when \( \Lambda^\text{erm} \gg \Lambda^\text{maml} \), where \( \Lambda^\text{erm}, \Lambda^\text{maml} \) are defined as the risk at globally optimal for ERM and MAML. In our setting, low zero-shot performance indicates a bad starting point in the loss landscape, which in turn, implies that the algorithms need more training samples to converge. Furthermore, given the fact that we are using the same sufficiently deep neural network for all algorithms, we have \( \Lambda^\text{erm} \approx \Lambda^\text{maml} \). Thus, according to the sample complexity bound above, initially harder problems impose larger sample complexity bound on MAML than on ERM, which may lead to MAML having insufficient data points to reach a good local optimum during few-shot transfer.

\(^2\)https://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html
Figure 3: Average accuracy on development sets (dashed line) and test sets (solid line) of five datasets. The x-axis shows the task configurations where \((N, T)\) refers to sampling \(T\) tasks for \(N\)-way classification. **Zeroshot** refers to zero-shot CLIP without any fine-tuning during either training or meta-testing. **Classical** refers to classical fine-tuning where we perform joint training on the entire training set. Both **FOMAML** and **MAMF** sample \(N\)-way \(T\) tasks during training. **MAMF** (red line) consistently outperforms **Classical** (orange line) on all datasets. On more challenging datasets where **Zeroshot** performance is lower, such as ClevrCounting and Fungi, **MAMF** outperforms **FOMAML**.

Figure 4: Ablation study on ClevrCounting dataset with fixed \(N = 5\) and varying \(T\). Both **MAMF** and **FOMAML** benefit from increasing the number of sampled tasks.

7 Conclusion

In this paper, we reformulate the traditional fine-tuning setting with *meta-testing* which emphasizes generalization on new tasks. We demonstrate the importance of uniform task sampling by proposing a simple yet effective fine-tuning method, **Model-Agnostic Multitask Fine-tuning**. Our algorithm consistently outperforms classical fine-tuning, and outperforms first-order MAML on initially more challenging tasks. We further show novel insight on the effectiveness of MAML in the context of few-shot transfer learning. Future work is needed to formally incorporate uniform task sampling into the generalization bound for transfer learning risk.

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Figure 6: Visualization of image embeddings of ClevrCounting dataset encoded by different model checkpoints. We use t-distributed Stochastic Neighbor Embedding (t-SNE) to visualize high-dimensional embedding of size 512. The visualization shows that the embedding of different classes from MAMF are more tightly clustered and mutually separated.

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