Deep Model Assembling

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Abstract

Large deep learning models have achieved remarkable success in many scenarios. However, training large models is usually challenging, e.g., due to the high computational cost, the unstable and painfully slow optimization procedure, and the vulnerability to overfitting. To alleviate these problems, this work studies a divide-and-conquer strategy, i.e., dividing a large model into smaller modules, training them independently, and reassembling the trained modules to obtain the target model. This approach is promising since it avoids directly training large models from scratch. Nevertheless, implementing this idea is non-trivial, as it is difficult to ensure the compatibility of the independently trained modules. In this paper, we present an elegant solution to address this issue, i.e., we introduce a global, shared meta model to implicitly link all the modules together. This enables us to train highly compatible modules that collaborate effectively when they are assembled together. We further propose a module incubation mechanism that enables the meta model to be designed as an extremely shallow network. As a result, the additional overhead introduced by the meta model is minimalized. Though conceptually simple, our method significantly outperforms end-to-end (E2E) training in terms of both final accuracy and training efficiency. For example, on top of ViT-Huge, it improves the accuracy by 2.7% compared to the E2E baseline on ImageNet-1K, while saving the training cost by 43% in the meantime. Code is available at https://github.com/LeapLabTHU/Model-Assembling.

1. Introduction

Recent years have witnessed a scaling-up of deep networks in the fields ranging from natural language understanding [8,31] and computer vision [9,43] to reinforcement learning [6,34]. Particularly, the development of foundation models [7,42] heavily relies on the success of large models. However, training these large models is challenging in many aspects. On the infrastructure side, centralized resources with strong computational and memory capacities are often required. Even so, the training of a single large model can still take weeks or even months to finish [11, 43]. On the optimization side, the training process tends to be unstable, difficult to converge, and vulnerable to overfitting [12].

A promising way to mitigate the above issues is adopting a divide-and-conquer strategy. In specific, we can first divide a large model into multiple sub-modules, and then train them independently. This strategy, which we refer to as modular training, can enable large models to be efficiently trained in a distributed manner. Moreover, it is also less likely to incur optimization issues than E2E training, since smaller sub-modules are much easier to optimize than the whole large model. After the distributed training process, ideally, we can reassemble the trained modules to obtain the target model. The basic idea is demonstrated in Figure 1.

Nevertheless, designing a proper modular training mech-
anism is non-trivial, as there exists a dilemma between independence and compatibility. Ideally, we expect that the modules can be trained independently to facilitate efficient distributed training. However, independently trained modules may have compatibility issues and yield inferior performance when assembled together. Some preliminary attempts along this direction only achieve partial independence to preserve compatibility. In specific, they mainly focus on decoupling the modules during back-propagation. For example, synthetic gradient based methods [10, 22] and delayed gradient based methods [21, 40] use approximated gradients to update each module. Local learning based methods [3, 4, 38] use specially designed local objectives to directly provide supervision signals for modules. By removing the cross-module dependency during back-propagation, they improve parallelization upon E2E training. However, these methods can only be seen as weakly modular training, since the modules are still highly dependent on each other during the forward propagation. Meanwhile, they have not exhibited the ability to train recently proposed large models (e.g., ViTs) effectively.

In this paper, we present a simple yet effective Model Assembling approach that attains modular training elegantly. This approach also enables us to effectively train large modules with high efficiency. There are two main ideas behind our method. First, to ensure the compatibility between the independently trained modules, we introduce a global, shared meta model to implicitly link all modules together. Second, to maximally reduce the additional overhead introduced by the meta model, we propose a module incubation mechanism to make the meta model cooperate with the target modules in a task-oriented way. As a result, we are able to use extremely shallow meta models which contain only one layer per module, without affecting the performance of the target model. The overview of our Model Assembling pipeline is presented in Figure 3.

We evaluate Model Assembling on ImageNet-1K [33] and CIFAR [23] with both Transformer and CNN-based architectures. Model Assembling is able to train large models with high training efficiency and data efficiency, meanwhile producing favorable results. For example, on ViT-H, Model Assembling outperforms E2E training by 2.7% with the training cost reduced by 43%. In low data regimes where only 25% of ImageNet-1K is available, Model Assembling effectively mitigates the overfitting issue of ViT-B and significantly outperforms E2E training by 7.2%.

2. Related Work

Model Parallelism divides a model into several modules and spreads them over multiple devices or nodes [24]. It is often used when a model is too large to fit into a single device. However, model parallelism may cause low resource utilization due to the sequential nature of the back-propagation algorithm. It can also induce a large communication overhead as more devices are used [16]. Several works have been proposed [15, 16, 20] to make model parallelism more efficient by introducing different kinds of pipeline mechanism. The modular training process in our method also divides a model into several modules. However, unlike model parallelism, modular training optimizes each module fully independently, thus being more efficient and enabling computational resources to be fully utilized.

Decoupled Learning of neural networks is receiving more and more attention due to its biological plausibility and its potential in accelerating the model training process and lowering the memory footprint. Auxiliary variable methods [1, 26, 35, 44] split the end-to-end optimization problem into sub-problems and achieve a certain level of decoupling with strong convergence guarantees. Another line of research [5, 25, 27, 30] uses biologically motivated methods to achieve decoupled learning. However, these methods have been shown to lack scalability [2]. Using auxiliary networks to achieve local supervision is also a way to achieve decoupling. For example, decoupled neural interfaces [22] propose using an auxiliary network to predict the error signal for a module, thus achieving decoupled learning. Local learning methods [3, 4, 38] use auxiliary classifiers to provide local supervision signals. Some other works [29, 39] further investigate decoupled learning in a self-supervised learning setting. There are also delayed gradient based methods [21, 40] which utilize delayed gradient to remove the direct dependency on subsequent modules and kernel machine-based methods [13]. To sum up, most above methods focus on decoupling modules during back-propagation, while the dependency between modules are still preserved during forward propagation. In contrast, our modular training process completely decouples the modules, enabling them to be trained in a distributed manner.

Knowledge Distillation [19] aims to train a small student model from the softened output of a larger model, thus encouraging the small model to imitate the behavior of the teacher model. In [32], the authors extend the idea of knowledge distillation to the feature level. Specifically, the authors propose to directly match the intermediate representations of the student network with the teacher model, thus encouraging the small model to imitate the teacher at the feature level. This kind of training process is similar to an important baseline of our method, which is called Module Imitation (see Figure 2 (b)). However, the main goal of knowledge distillation is model compression, with a smaller model imitating the behavior of a larger model. In contrast, Module Imitation aims at making independently trained modules compatible with each other, with a larger model imitating the behavior of a smaller model.
3. Model Assembling

As aforementioned, training large models in an end-to-end manner is typically challenging, e.g., the learning process tends to be unstable, resource/data-hungry, and vulnerable to overfitting. To address these issues, we propose a divide-and-conquer strategy called Model Assembling. At the core of Model Assembling is a modular training process, which we will elaborate in this section.

**Modular Training** first divides a large model into smaller modules, and then optimizes each module independently. As modern neural networks are generally constituted by a stack of layers, it is natural to divide the model along the depth dimension. Formally, given a large target model $M$ with $n$ layers, we can divide $M$ into $K (K \leq n)$ modules:

$$M = M_K \circ M_{K-1} \circ \cdots \circ M_1, \quad (1)$$

where $\circ$ represents function composition. Then, each module $M_i$ is trained independently in modular training.

In this way, the cumbersome task of directly training a large model is decomposed into easier sub-tasks of training small modules. More importantly, these sub-tasks can be distributed to different machines and executed in full parallel, with no communication needed. After this process, we can simply reassemble the trained modules, thus avoiding training the large model directly from scratch.

Therefore, if implemented properly, modular training can be a highly effective and efficient way for large model training. However, designing a proper modular training mechanism is a non-trivial task. In the following, we discuss in detail the challenges and present our solutions.

**Dilemma I: Independence vs. Compatibility.** At the core of modular training is the requirement of independence, which enables each module of a large model to be trained in a distributed manner. However, if the modules are trained completely unaware of other modules, they may have low compatibility between each other, hence negatively affecting the performance of the assembled model.

**Solution: Meta Model.** We argue the root of the above dilemma is that, the requirement of independency prevents the explicit information exchange between modules. Consequently, the modules cannot adapt to each other during training, causing the incompatible issue. Driven by this analysis, we propose to address the dilemma by introducing a global, shared meta-model $\hat{M}_i^*$ to enable implicit information exchange between the modules. Notably, the meta model $\hat{M}_i^*$ is designed to have the same number of modules as the target model $M$:

$$\hat{M}_i^* = M_K \circ \hat{M}_{K-1} \circ \cdots \circ \hat{M}_1, \quad (2)$$

and is pre-trained on the training dataset.

With the help of the meta model $\hat{M}_i^*$, we can easily obtain compatible modules. For example, we can let each target module $M_i$ imitate the behavior of meta module $\hat{M}_i^*$ by feeding it the same input as $\hat{M}_i^*$, and optimize it to produce feature similar to the output of $\hat{M}_i^*$. In this way, we can obtain compatible target modules due to the inherent compatibility between the pre-trained meta modules, thus resolving the first dilemma. We refer to this process of modular training as Module Imitation. In an oracle case where $\hat{M}_i^*$ has the same architecture as $M$ (Figure 2 (a)), this process can directly produce a good approximate of a well-learned target model when the trained modules are assembled.

**Dilemma II: Efficiency vs. Efficacy.** Nevertheless, the solution in Figure 2 (a) may be impractical. Since our motivation is to train $M$, it is unreasonable to assume a well-learned meta model $\hat{M}_i^*$ of the same size as $M$ is already available. More importantly, adopting a large $\hat{M}_i^*$ to facilitate modular training can incur unaffordable additional overhead, which makes the training process extremely inefficient. Therefore, in practice, a small meta model needs to be adopted for efficiency, as illustrated in Figure 2 (b). However, small meta models may have insufficient representation learning ability, and thus may limit the performance of the final model. From this perspective, the meta model should not be too small for the efficacy of modular training.

**Solution: Module Incubation.** We argue that the above dilemma comes from the inappropriate optimization objective for the target module $M_i$, which is to strictly imitate the meta module $\hat{M}_i^*$. This objective makes the representation learning ability of $M_i$ bounded by $\hat{M}_i^*$. Therefore, we propose a Module Incubation mechanism to better leverage the meta model for modular training. In specific, instead of letting $M_i$ strictly imitate $\hat{M}_i^*$, we encourage $M_i$ to cooperate with the meta model $\hat{M}_i^*$ to attain a task-oriented learning goal. Formally, we replace the $i$-th module in the
meta model \( \hat{M}^* \) with \( M_i \), obtaining a hybrid network \( \hat{M}^{(i)} \):

\[
\hat{M}^{(i)} = \hat{M}_{i}^{K} \circ \cdots \circ \hat{M}_{i+1}^{i} \circ M_{i} \circ \hat{M}_{i-1}^{i} \circ \cdots \circ \hat{M}_{i}^{1}.
\]  

(3)

Then we fix \( \hat{M}_{i}^{j} (j \neq i) \), and thus the outputs of \( \hat{M}^{(i)} \) corresponding to the input \( x \) can be defined as a function of \( M_i \), namely:

\[
x \rightarrow \hat{M}^{(i)}(x; M_i).
\]  

(4)

Finally, we can directly minimize an end-to-end loss \( \mathcal{L}_{E2E}(\cdot) \) with respect to \( \hat{M}^{(i)}(x; M_i) \):

\[
\text{minimize } \mathcal{L}_{E2E}(y, \hat{M}^{(i)}(x; M_i)),
\]  

(5)

where \( y \) is the label of the input \( x \). Here, \( \mathcal{L}_{E2E}(\cdot) \) can be defined conditioned on the task of interest. In this paper, we mainly consider the standard cross-entropy loss in the context of classification problems. The above process can be seen as using the pre-trained meta model \( M^* \) to “incubate” the target module \( M_i \), and thus we call this way of modular training “Module Incubation”.

Unlike Module Imitation, here we enforce \( M_i \) to cooperate with \( \hat{M}_{i}^{j} (j \neq i) \) to accomplish the final task. Therefore, \( M_i \) is encouraged to take full advantage of its potential. Since \( M_i \) is often larger than \( \hat{M}_{i}^{*} \), it can acquire stronger ability than \( \hat{M}_{i}^{*} \) in terms of representation learning. In contrast, the ability of \( M_i \) is generally limited by the insufficient meta module \( \hat{M}_{i}^{*} \) in Module Imitation. Empirical evidence is also provided in Figure 9 to support this point.

Interestingly, we find that smaller meta models actually bring better performance in Module Incubation (see Figure 8). This intriguing phenomenon provides a favorable solution to the second dilemma, i.e., we can directly use the shallowest meta model to incubate the modules. In our implementation, to get both efficiency and efficacy, we simply design the meta model to have only one layer\(^1\) per module.

**Algorithm 1** The Model Assembling Algorithm

**Require:** Initialize the target model \( M = M_{K} \circ M_{K-1} \circ \cdots \circ M_{1} \);

1: Training dataset \( \mathcal{D} \)
2: Pre-train \( \hat{M} \) on \( \mathcal{D} \) to obtain \( M^* \)
3: for \( i = 1 \) to \( K \) do
   4:   Construct \( \hat{M}^{(i)} \) by replacing \( \hat{M}_{i}^{*} \) in \( M^* \) with \( M_i \)
   5:   Minimize \( \mathcal{L}_{E2E}(y, \hat{M}^{(i)}(x; M_i)) \) on \( \mathcal{D} \) to obtain \( \hat{M}_{i}^{*} \)
4: end for
5: Assemble the target model \( M^{\text{assm}} = M_{K} \circ M_{K-1} \circ \cdots \circ M_{1} \)
6: Fine-tune \( M^{\text{assm}} \) on \( \mathcal{D} \) to obtain the final model \( M^{*} \)

**Assemble the Target Model.** After all the modules \( M_i (i \in \{1, \ldots, K\}) \) are trained, we obtain the target model by assembling them:

\[
M^{\text{assm}} = M_{K} \circ M_{K-1} \circ \cdots \circ M_{1}^{*},
\]  

(6)

where \( M_{1}^{*} \) denotes the modular-trained target module. Then, we fine-tune \( M^{\text{assm}} \) to obtain the final model \( M^{*} \). The fine-tuning process further unleashes the representation learning power of the target model. However, this does not downplay the importance of our modular training process. We comprehensively discuss the importance of modular training in Figure 7 and the effects of the fine-tuning process in Figure 10, please refer to Section 4.4 for more details. Together, we summarize our Model Assembling pipeline in Algorithm 1 and Figure 3.

**4. Experiments**

This section presents a comprehensive experimental evaluation on ImageNet-IK [33] and CIFAR [23] to vali-
Table 1. Training large ViT models on ImageNet-1K. ↑: Our reproduced baselines. Training cost is measured in A100 GPU Hours.

| Model       | Image Size | FLOPs | #Param | Top-1 Acc. | Top-1 Acc. | Top-1 Acc. | Training Cost (GPU Hours) |
|-------------|------------|-------|--------|------------|------------|------------|--------------------------|
|             |            |       |        | E2E-ViT [12] | E2E-DeiT [36] | E2E [17] | DeiT + Ours | E2E-ViT/DeiT | E2E [17] | DeiT + Ours |
| ViT-B       | 224²       | 17.6G | 87M    | -          | 81.8%       | 82.3%      | 82.4%         | 0.29K        | 0.29K      | 0.39K       |
|             | 384²       | 55.5G | -      | 77.9%      | 83.1%       | -          | 83.7%         | 0.45K        | -          | 0.55K       |
| ViT-L       | 224²       | 61.6G | 304M   | -          | 81.4%↑      | 82.6%      | 83.9%         | 1.09K        | 0.72K      | 0.89K       |
|             | 384²       | 191.1G| -      | 76.5%      | 83.3%↑      | -          | 85.3%         | 1.58K        | -          | 1.38K       |
| ViT-H       | 224²       | 167.4G| 632M   | -          | 81.6%↑      | 83.1%      | 84.3%         | 4.79K        | 3.19K      | -           |
|             | 392²       | 545.3G| -      | -          | 83.4%↑      | -          | 85.6%         | 6.90K        | -          | 4.83K       |

Table 2. Results on CIFAR-100. The results on DeiT [36], InfoPro [38] and DGL [4] are based on our implementation. We adjust the patch size of ViT to 4 × 4 for the smaller image size on CIFAR. Training cost is measured in A100 GPU Hours.

| Model       | Image Size | FLOPs | #Param | Top-1 Acc. | Top-1 Acc. | Top-1 Acc. | Training Cost (GPU Hours) |
|-------------|------------|-------|--------|------------|------------|------------|--------------------------|
|             |            |       |        | E2E-DeiT [36] | InfoPro [38] | DGL [4] | DeiT + Ours | E2E-DeiT | E2E [17] | DeiT + Ours |
| ResNet-110  | 32²        | 0.3G  | 1.7M   | 71.1%      | 71.2%       | 69.2%      | 73.0%         | 2.0         | 2.1        | 2.1         |
| DeiT-T-32   | 32²        | 1.0G  | 14.5M  | 72.8%      | 73.7%       | 72.0%      | 75.3%         | 1.8         | 2.0        | 2.0         |
| DeiT-T-128  | 32²        | 3.9G  | 57.2M  | 69.4%      | 73.2%       | 70.9%      | 77.2%         | 7.2         | 7.4        | 7.4         |

Figure 4. Training efficiency (accuracy vs. training wall-time) of ViT-Large (left), ViT-Huge (middle) on ImageNet-1K and DeiT-Tiny-128 on CIFAR-100 (right). Different points correspond to different training budgets (i.e., with varying numbers of epochs).

4.1. Main Results

Training large models on ImageNet-1K. Since the results of ViT-L and ViT-H are not reported in DeiT [37], and directly adopting the original training configurations results in optimization issues, we report our reproduced baselines. Besides the re-adjusted stochastic depth rates, we also adopt the LAMB [41] optimizer and a uniform stochastic depth rate following [37] to further improve E2E training.

As shown in Table 1, our method consistently improves the performance of models on the top of E2E-DeiT for all the three ViT variants, and shows more advantage for training larger models. Specifically, on ViT-H, our method outperforms E2E-DeiT by 2.7% while being 43% faster. The advantage continues when the models are fine-tuned at higher resolution, where our method outperforms E2E-DeiT by 2.0% and 2.2% for ViT-L and ViT-H, respectively.

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We also compare Model Assembling with the recently proposed improved E2E baselines in [17], where a systematically hyper-parameter search is performed on training configurations. Notably, this comparison places our method at a disadvantage since we directly adopt the configurations of E2E-DeiT, which may be sub-optimal for our method. Even so, Model Assembling still performs better.

It is also noteworthy that, as discussed in Section 3, our modular training enables different parts of a large model to be trained on different machines, with no communication needed. This feature is of great importance in scenarios where the machines are highly heterogeneous in their computation and communication abilities. In these cases, the slowest machine may become the bottleneck of the overall progress for conventional distributed training, while our modular training will not be affected by this issue.

Results on CIFAR. On CIFAR-100, we test our method on both ViTs and CNNs. For ViTs, we adopt two DeiT-Tiny [36] models with a depth of 32 and 128. For ResNet-110, we adopt $K = 3$ and a meta model with 3 residual layers. Two strong modular learning methods, i.e., InfoPro [38] and DGL [4], are also considered as our baselines. The results are presented in Table 2. The basic trend is similar to the results on ImageNet-1K, where our method consistently outperforms E2E training and other baselines, with larger advantages for larger models. For example, on DeiT-T-128, our method outperforms the E2E baseline by 7.8% with 17% speedup on training wall-time, and outperforms the stronger baseline InfoPro by 4% with 19% speedup.

Higher computational efficiency for training. In Figure 4, we present a more comprehensive comparison of the training efficiency between our method and the E2E baselines. We adjust the training cost budget by varying the number of epochs. One can observe that our method shows a better efficiency-accuracy trade-off than all E2E baselines, including the recently proposed improved E2E baselines [17]. For fair comparisons, we further discuss the benefits of our method on training efficiency by comparing it with E2E-DeiT since they adopt the same training configurations. On ViT-L and ViT-H, our method requires $3.2 \times$ and $4.1 \times$ less training cost, respectively, while achieving competitive performance compared to E2E-DeiT. We also present detailed convergence curves of ViT-H in Figure 5. For our method, we plot the convergence curve starting from the assembled models. Notably, the starting points of our convergence curves are higher than the convergence curve of E2E training. This demonstrates the high compatibility between the modules trained by our method.

Higher data efficiency. Another important advantage of our method is its higher data efficiency, i.e., it is able to dramatically outperform the E2E baselines when training data are relatively scarce. To demonstrate this, we sample two class-balanced subsets of ImageNet-1K, containing 25% and 50% of the training data, and train ViT-B on them. The training cost is kept the same as full-set training by us-

| Training Cost (GPU Hours) | ImageNet-Acc (%) | E2E-DeiT | DeiT + Ours | Meta Model Pre-training (300 epochs) | Assembled Models | E2E Training (300 epochs) |
|---------------------------|------------------|----------|-------------|--------------------------------------|------------------|--------------------------|
| 0                         | 50+50            | 80.5     | 83.4        | 84.3                                 | 81.6             | 82.4%                    |
| 25                        | 25+25            | 82.3     | 83.2        | 84.3                                 | 81.6             | 81.6%                    |
| 100                       | 100+100          | 88.0     | 88.4        | 88.8                                 | 81.6             | 82.4%                    |

Figure 5. Convergence curves of ViT-Huge. We compare 3 training schedules of our method with E2E-DeiT [36] trained for 300 epochs. For our method, we use $m+n$ to indicate the modular training epochs and the fine-tuning epochs, respectively.

The training loss is kept the same as full-set training by us-

| Training | Top-1 Acc. | Training Loss |
|----------|------------|---------------|
| E2E-DeiT [36] | DeiT + Ours | E2E-DeiT [36] | DeiT + Ours |
| 100% IN-1K | 81.8% | 82.4% (10.6) | 2.63 | 2.69 |
| 50% IN-1K | 74.7% | 78.6% (13.9) | 2.34 | 2.55 |
| 25% IN-1K | 65.7% | 72.9% (17.2) | 2.09 | 2.41 |

Table 3. Training ViT-B with fewer training samples (IN-1K: ImageNet-1K). Here, we sample 2 class-balanced subsets from ImageNet-1K. The training loss in the last epoch is also reported.

4.2. Designing Deeper Models

With our proposed method, we can further explore an interesting question: in current transformer models, is the ratio of depth v.s. width optimal? The answer may be true in the context of E2E learning. Previous work [14, 45] conjecture that deeper ViTs trained in an end-to-end manner may have the over-smoothing problem, hindering their performance and hence it is not suggested to make ViTs deeper than their current design.

To investigate this problem, we progressively increase the depth of a DeiT-Tiny in Figure 6, and train them on CIFAR-100 to evaluate their performance. One can observe that the performance of E2E learning quickly satu-
Table 4. **Training deep-narrow models.** Here, a deep-narrow version of ViT-B is designed (denoted as ‘ViT-B-DN’) by doubling the depth of ViT-B with the FLOPs unchanged.

| Model       | FLOPs | #Param | Depth | Width |
|-------------|-------|--------|-------|-------|
| ViT-B       | 17.6G | 87M    | 12    | 768   |
| ViT-B-DN    | 17.7G | 85M    | 24    | 540   |

Table 5. **Learning with distributed training sets** (DistData). IN-1K: ImageNet-1K; C100: CIFAR-100. Here, the training set is divided into 4 subsets, and each module is trained on one subset.

| Method                                      | IN-1K / ViT-B | C100 / DeiT-T-128 |
|---------------------------------------------|---------------|--------------------|
| E2E-DeiT [36]                              | 81.8%         | 69.4%              |
| DeiT + Ours                                | 82.4% (10.6%) | 77.2% (77.8%)      |
| DeiT + Ours (DistData)                     | 82.2% (10.4%) | 74.8% (75.4%)      |

In this scenario. We first pre-train the meta model with the full training set. Then, we divide the training set into 4 non-overlapping subsets in a class-balanced manner, and distribute the subsets along with the pre-trained meta model to 4 machines. In this way, each machine can train one module with its cached subset. We keep the total number of training iterations unchanged during modular training. Finally, we collect the trained modules and fine-tune the assembled model on the full training set. The results are presented in Table 5 (denoted as DistData). On both ImageNet and CIFAR-100, Model Assembling can still achieve decent performance despite that only 25% of the data is available to each machine.

### 4.4. Discussion

In this section, we provide a more comprehensive analysis of our method. Unless mentioned otherwise, we use DeiT-T-128 as our target model and conduct experiments on CIFAR-100 dataset.

![Proportion of modular training](image)

**Proportion of modular training.** The proportion is measured by the wall-clock time of modular training in the whole pipeline of Model Assembling. When the proportion of modular training is zero, our method reduces to E2E training.

**Importance of modular training.** The core of Model Assembling is the modular training process. Therefore, we provide an analysis of its importance. In specific, we keep the overall training cost fixed, and progressively increase the proportion of modular training. The proportion is measured by the wall-clock time of modular training in the whole pipeline of Model Assembling. We present the results in Figure 7, where different lines correspond to different overall training costs. Note that our method reduces to E2E training when the proportion of modular training reduces to zero. It can be seen that introducing modular...
training significantly boosts the performance of the model. Furthermore, our method outperforms E2E training within a wide range of modular training proportions, demonstrating the robustness of our method.

**Depth of the meta model.** In Figure 8, we present our ablation on the depth of the meta model. The accuracy of our method is depicted in a red line, where the horizontal axis denotes the number of layers of the meta model. An intriguing observation can be obtained from Figure 8, *i.e.*, our method achieves high accuracy even with a surprisingly shallow meta model (*e.g.*, 4 layers, one for each module). One possible explanation for this phenomenon is that, during the module incubation process, adopting shallower meta models makes the supervision information flow more easily toward the target module, and thus the target modules can be trained more thoroughly and converge faster.

![Figure 8. Depth of the meta model.](image)

**Comparisons with Module Imitation.** Figure 8 also presents the results of Module Imitation (Figure 2 (b)), where we adopt $L_1$ distance as the loss function in feature space. It can be seen that our method consistently outperforms Module Imitation, especially when the meta model is small. This is aligned with our intuition in Section 3 that the cooperative nature of Module Incubation prevents the representation learning power of $M_i$ from being limited by an insufficient meta model. We also explicitly measure how well a trained target module $M_i^*$ supports a meta model to learn representations by replacing the meta module $M_i^*$ in the meta model with $M_i^*$. The accuracy gain of this hybrid model over the original meta model, which is DeiT-T-4, is evaluated. As the results in Figure 9 show, the modules trained by Module Incubation (ours) do provide better support for the meta model by leveraging its stronger ability in representation learning.

![Figure 9. Accuracy gain](image)

**Sensitivity Test.** We further conduct a sensitivity test on the hyper-parameters for fine-tuning the assembled model, namely, the epochs and the learning rate for fine-tuning. The results are shown in Figure 10, where we use DeiT-T-128 as the target model. Three important observations can be obtained. First, our method can outperform E2E training even if the model is only fine-tuned for one epoch (71.2% for ours *v.s.* 69.4% for E2E), which clearly demonstrates the necessity of our modular training process. Second, the majority of the performance gain can be obtained by fine-tuning the assembled model for a short period (*e.g.*, 20 epochs), and further prolonging the fine-tuning phase gives diminishing returns. Third, the performance of our method is generally robust to the choice of the learning rate of fine-tuning. For a moderate period of fine-tuning, directly choosing the default learning rate is enough. Therefore, for all the experiments, we do not tune this learning rate to keep the simplicity of our method.

**Number of Modules $K$.** Finally, we also present our study on $K$, which is the number of modules when we divide a target model. The results are presented below:

| Model     | $K = 2$ | $K = 4$ | $K = 8$ | $K = 16$ | E2E |
|-----------|---------|---------|---------|----------|-----|
| DeiT-T-32 | 72.3%   | 76.1%   | 75.6%   | 75.6%    | 72.8% |
| DeiT-T-256| 70.9%   | 76.7%   | 77.2%   | 75.0%    | 66.9% |

It can be seen that the optimal value of $K$ differs for models of different depths, and the deeper model prefers a larger $K$. This is reasonable since gradient vanishing and other optimization problems get more severe for deeper models, and thus a finer division of the model is needed.

**5. Conclusion**

This paper presented Model Assembling, which trains a large model in a divide-and-conquer manner. Specifically, it
divides a large model into smaller sub-modules, trains them independently, and then reassembles them together. By introducing a lightweight meta model to incubate modules, Model Assembling can effectively train compatible modules with high efficiency. Meanwhile, Model Assembling enables fully distributed workflow during modular training, \( i.e. \), the model itself and even the training data can be distributed to different machines. Although conceptually simple, our method can outperform end-to-end training dramatically in terms of both computational and data efficiency without optimization issues.

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