Masking meets Supervision: A Strong Learning Alliance

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Abstract

Pre-training with random masked inputs has emerged as a novel trend in self-supervised training. However, supervised learning still faces a challenge in adopting masking augmentations, primarily due to unstable training. In this paper, we propose a novel way to involve masking augmentations dubbed Masked Sub-branch (MaskSub). MaskSub consists of the main-branch and sub-branch, the latter being a part of the former. The main-branch undergoes conventional training recipes, while the sub-branch merits intensive masking augmentations, during training. MaskSub tackles the challenge by mitigating adverse effects through a relaxed loss function similar to a self-distillation loss. Our analysis shows that MaskSub improves performance, with the training loss converging faster than in standard training, which suggests our method stabilizes the training process. We further validate MaskSub across diverse training scenarios and models, including DeiT-III training, MAE finetuning, CLIP finetuning, BERT training, and hierarchical architectures (ResNet and Swin Transformer). Our results show that MaskSub consistently achieves impressive performance gains across all the cases. MaskSub provides a practical and effective solution for introducing additional regularization under various training recipes. Code available at https://github.com/naver-ai/augsub

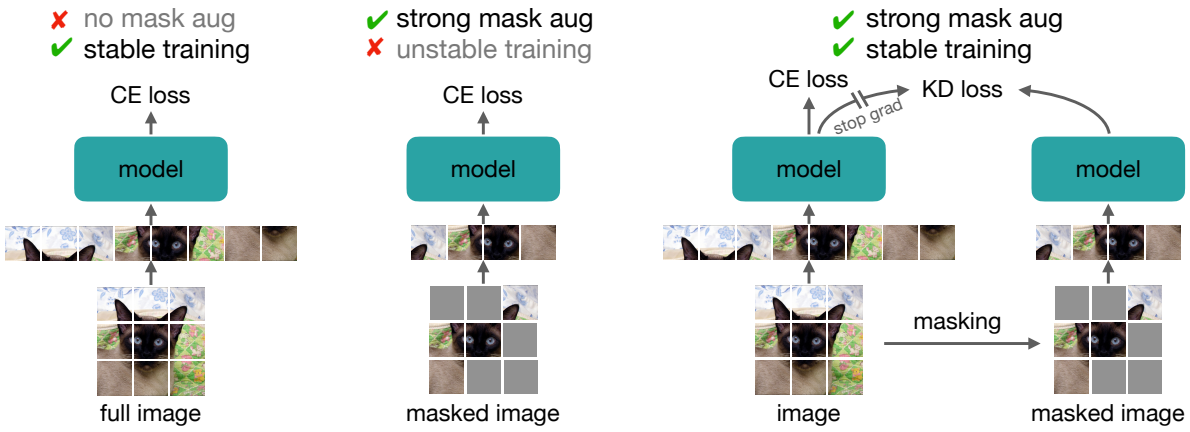
1. Introduction

Supervised learning is the most basic and effective way to train a network to achieve high performance on a target task. To improve supervised learning, diverse regularizations are developed and used as training recipes [36, 37, 44], which represent a group of sophisticatedly tuned regularizations to maximize learning performance. Supervised learning has always held an advantage over self-supervised learning [2, 4] based on the benefit of supervision. However, emergence of Vision Transformer (ViT) [9] and Masked Image Modeling (MIM) [1, 15, 30] is changing this trends. ViT, which lacks inductive bias compared to convolution networks, poses many challenges to generalization performance for supervised learning. On the other hand, MIMs such as MAE [15] rise as an alternative pretraining method for ViT by achieving competitive performance with supervised learning recipes. Although a recent study [37] shows that new supervised learning outperforms MIMs, the gap is insignificant. Thus, MIMs are still a strong competitor of supervised learning methods.

MIM masks random areas of an input image and forces the network to infer the masked area using the remaining area. A representative part of MIM is high mask ratios over 50%. Although MIM also works at small mask ratios, it shows remarkable performance when trained with a high mask ratio. The high mask ratio is a major difference between MIM and supervised learning since this high mask ratio, over 50%, is not beneficial in supervised learning. Supervised learning also has utilized random masking as an augmentation [11, 56], but it significantly degrades performance when the masking ratio is high. In other words, supervised learning is not applicable for strong masking augmentation. We conjecture that it is a major problem of the current supervised learning recipe, and there is room for improvement by enabling strong masking.

Our goal is to improve supervised learning with strong mask augmentation over 50%. To this end, we introduce a novel learning framework using a "sub-branch" alongside the main-branch; throughout this paper, we use the term "sub-branch" to describe a model with dropped inputs. The main-branch uses standard training recipes [37, 44], while the sub-branch utilizes mask augmentation. We name our method as Masked Sub-branch (MaskSub).

We visualize the overview of MaskSub in Figure 1. We consider a high masking ratio over 50% as similar in MAE [15]. Figure 1 (b) shows that applying the strong random masking on the main-branch may lead to degraded performance. In contrast, as in Figure 1 (c), MaskSub leverages the sub-branch for random masking, and the sub-branch receives the training signal from the main-branch similar to the self-distillation [32, 52, 58]. While the random masking technique amplifies the difficulty of the training process, this is counterbalanced by self-distillation loss since the outputs of the main-branch are relaxed and easy-to-learn objective than the ground-truth label. In summary, MaskSub ap-



(a) Standard training (b) Mask augmentation (c) **MaskSub** training

Figure 1. **Overview of Masked Sub-branch (MaskSub).** (a) standard supervised training; (b) masking augmentation training. The masking is applied to the main model, which degrades performance; (c) our **MaskSub** training, which separates the masking from the main model using the sub-branch and relaxes loss with self-distillation. MaskSub substantially improves the state-of-the-art training recipes [37, 44].

plies a mask augmentation separated from the main-branch, utilizing a relaxed loss form.

We analyze MaskSub using 100 epochs training on ImageNet [6]. Without MaskSub, loss convergence speed and corresponding accuracy are significantly degraded when mask augmentation is applied. Conversely, MaskSub mitigates potential harmful effects from additional regularization, leading to a network training process that is even more efficient than standard training procedures. Also, MaskSub is not limited to mask augmentation and can be used for general drop regularizations. As a result, MaskSub is expanded to any random drop regularization without disrupting the convergence of original train loss; we employ three in-network drop-based options to show the applicability: masking [1, 15], dropout [35], and drop-path [10, 19]. Corresponding to each respective regularization strategy, we denote them MaskSub, DropSub, and PathSub. Among the three variants, MaskSub notably exhibits a remarkable performance enhancement, demonstrating the necessity of mask augmentation in supervised learning.

We extensively validate the performance of MaskSub. MaskSub is applied on various state-of-the-art supervised learnings including DeiT-III training [37], MAE finetuning [15], BEiTv2 finetuning [30], CLIP finetuning [8], BERT training [7], ResNet-RSB [44], and Swin transformer [27]. MaskSub demonstrates remarkable performance improvement in all benchmarks. We argue that MaskSub can be regarded as a novel way to utilize regularization for visual recognition.

2. Related Work

Training recipe has been considered an important ingredient in building a high-performance network. He et al. [16] demonstrate that the training recipe significantly influences the network performance. RSB [44] is a representative and high-performance recipe for ResNet. With the emergence of ViT [9], the training recipe for ViT has gained the attention of the field. DeiT [36] shows that ViT can be trained to display strong performance with only ImageNet-1k [6]. DeiT-III [37] is an improved version of DeiT, which applies findings from RSB to DeiT instead of distillation from CNN teacher. It is challenging to implement stronger or additional regularization in existing training recipes. To address this issue, we propose our MaskSub employing sub-branchs.

CoSub [38] introduces a similar concept to ours, utilizing sub-branchs. However, the sub-branch objective differs: while MaskSub aims to stabilize training through additional regularization, CoSub aims to train the sub-branchs by co-training [55]. We regard MaskSub as a more generalized framework since CoSub only considers the drop-path method to employ sub-branchs, whereas MaskSub can cover various drop-based techniques, including masking.

Self-distillation utilizes supervision from a network itself instead of using a teacher. ONE [58] uses a multi-branch ensemble to build superior output for the network and distill ensemble outputs as supervision for each branch. Some studies [32, 52] utilize the early-exit network for self-distillation. Those studies improve performance by using an entire network as a teacher and an early exit network as a student. MaskedKD [34] utilizes masking to reduce computation for knowledge distillation. From a self-distillation perspective, MaskSub presents a new insight into constructing the student model (i.e., sub-branch) from the teacher model (i.e., main-branch) utilizing drop-based techniques. Note that most self-distillation studies are not compatible with recent training recipes [37, 44]. Thus, the general applicability of MaskSub is a notable contribution.

Self- and semi-supervised learning share components

with MaskSub. Contrastive learning incorporates two models with self-distillation loss [3, 12]. Want et al. [41] introduce a double tower with weak and strong augmentation for each model. MAE [15] uses masked image reconstruction as self-supervision, and supervised MAE [26] introduces supervised learning as an additional task for MAE. MAE and supMAE aim to reconstruct masked images using MAE training recipe, rather than supervised learning. In contrast, MaskSub only relies on label-related loss with a supervised learning recipe. In semi-supervised learning, UDA [47] introduces a two-branch framework, similar to the main- and sub-branch in MaskSub. However, MaskSub is more computationally efficient by using masking [15] and removing label-consistency checks for unlabeled data. Also, MaskSub extends the two-branch framework to supervised learning via distillation loss, in contrast to UDA's consistency loss. While these studies share the fundamental concept with MaskSub and inspired our work, the training techniques for supervised learning differ from those in semi- and self-supervised learning. Thus, we argue that MaskSub retains its originality and novelty compared to these studies.

3. Method

We propose our method Masked Sub-branch (MaskSub) with formulation and pseudo-code in Section 3.1. Section 3.2 presents analyses of MaskSub with loss convergence, accuracy, and gradient. In Section 3.3, we introduce variants of MaskSub: DropSub, and PathSub.

3.1. Masked Sub-branch (MaskSub)

The cross-entropy loss with the softmax $\sigma(\mathbf{z}) = e^{z_i}/\sum_j e^{z_j}$ for images $\mathbf{x}_i$ and one-hot labels $\mathbf{y}_i (i \in [1, 2, ..., N])$ in a mini-batch with size N is denoted as

$$-\frac{1}{N}\sum_{i}^{N}\mathbf{y}_i \log\left(\sigma(f_\theta(\mathbf{x}_i|r_{\text{mask}}=0))\right), \tag{1}$$

where f_θ represents the network used for training. r_{mask} means a ratio of masked patches in an input image. Since the masking ratio can be easily changed, we denote it as a condition for network function. Based on the value of r_{mask}, certain network features are dropped with probability r_{mask}. Note that we set the default masking ratio to zero for convenience. Then, loss for masking ratio $r \in [0, 1]$ is

$$-\frac{1}{N}\sum_{i}^{N}\mathbf{y}_i \log\left(\sigma(f_\theta(\mathbf{x}_i|r_{\text{mask}}=r))\right). \tag{2}$$

Typically, a network with mask augmentation is trained with Eq. (2). But, we conjecture that training using Eq. (2) with a high masking ratio (*i.e.* $r \geq 0.5$) may interfere with loss convergence and induce instability in training. To ensure training stability, we utilize the model output of equation Eq. (1), $f_\theta(\mathbf{x}_i|r_{\text{mask}}=0)$, as guidance for masking augmentation $f_\theta(\mathbf{x}_i|r_{\text{mask}}=r)$ instead of $\mathbf{y}_i$. In other words, Eq. (2) is changed as

$$-\frac{1}{N}\sum_{i}^{N}\sigma(f_\theta(\mathbf{x}_i|r_{\text{mask}}=0)) \log\left(\sigma(f_\theta(\mathbf{x}_i|r_{\text{mask}}=r))\right). \tag{3}$$

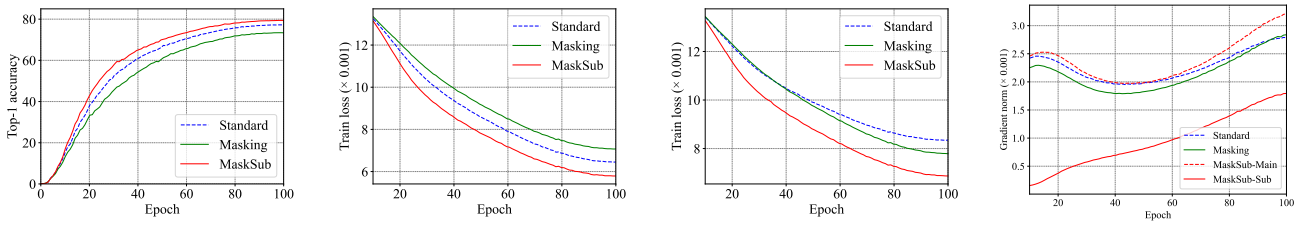
In our Masked Sub-branch (MaskSub), the average of Eq. (1) and Eq. (3) is used as a loss function for the network. We designate $f_\theta(\mathbf{x}_i|r_{\text{mask}}=0)$ as the main-branch and $f_\theta(\mathbf{x}_i|r_{\text{mask}}=r)$ as the sub-branch. This naming convention is employed because a network with masked inputs appears to be a subset of the entire network. In Eq. (3), the main-branch output $f_\theta(\mathbf{x}_i|r_{\text{mask}}=0)$ is used with stop-gradient. Thus, the sub-branch is trained to mimic the main model, but we want the gradient for the main-branch to be independent of the sub-branch. This can be interpreted as self-distillation, where knowledge is transferred from the teacher (main-branch) to the student (sub-branch). Note that MaskSub can easily be expanded to binary cross-entropy loss by replacing the softmax function with the sigmoid function, which is used for recent training recipes [37, 44].

Algorithm 1 MaskSub in PyTorch-style pseudo-code

```
for (x, label) in data_loader:
    o1 = f(x)          # main
    o2 = f(mask(x,r)) # sub (mask ratio: r)
    loss1 = CE(o1, label) / 2
    loss2 = CE(o2, softmax(o1.detach())) / 2
    (loss1+loss2).backward()
    optimizer.step()
```

Algorithm 1 describes PyTorch-style pseudo-code of training with MaskSub. The masking ratio is put into the network input. The gradients are calculated on the main and sub-branch average losses. Note that MaskSub does not use any additional data augmentation, optimizer steps, and network parameters for the sub-branch. We use MAE-style random masking [15], removing masked tokens to reduce computation costs by default. It significantly reduces the training cost of MaskSub. Approximately, MaskSub with 50% masking requires $\times 1.5$ computation to standard training. In practical implementation, we separate the main and sub-branch backward passes utilizing the gradient accumulation of PyTorch. So, VRAM for the main-branch can be released before the sub-branch computation, which eliminates the need for additional VRAM for MaskSub training. We will show the impact of MaskSub on diverse cases in Section 4, including computation analysis in Section 4.5.

MaskSub automatically controls the difficulty of the sub-branch. If the main-branch is close to the ground-truth label, the sub-branch loss aims to attain the ground-truth label under masking. Conversely, if the main-branch fails to converge, the sub-branch loss becomes easy. This difficulty design is inspired by distillation studies [5, 20, 28]. The



(a) Accuracy (b) Train loss (standard) (c) Train loss (masking) (d) Gradient norm

Figure 2. **MaskSub training analysis**. We use 50%-random masking to compare three training settings: standard Eq. (1), masking Eq. (2), and MaskSub. We visualize (a) validation accuracy; (b) train loss without masking; (c) train loss with masking; (d) gradient norm.

distillation becomes difficult when a high-performance network is used as a teacher [5, 28]. An early-stage network is easy, and an end-stage network is challenging [20]. Thus, MaskSub can be considered as a sample-wise masking augmentation that is exclusively applied to images that produce successful output in the main-branch.

3.2. Analysis

We analyze MaskSub with ViT-B [9] for 100 epochs training on ImageNet-1k [6]. Based on DeiT-III [37], we shorten the epoch to 100 epochs and use image resolution 224×224. We compare three settings: standard, masking, and MaskSub. The standard uses Eq. (1) as the training loss, and masking augmentation is not used. For the masking setting, the network is trained with Eq. (2). Note that it is a common practice to use a regularization or an augmentation in supervised learning. We compare those two settings with MaskSub. For analysis, we measured Eq. (1) 'train loss - standard' and Eq. (2) 'train loss - masking'. It shows how losses changed by training setting.

Figure 2 shows loss and accuracy trends in random masking 50% (*i.e.*, $r_{mask} = 0.5$) case. When random masking is applied to training (green), the masking loss (Figure 2c) converges better than the standard (blue). However, it significantly degrades the standard train loss (Figure 2b), resulting in a drop in accuracy (Figure 2a). Regularization over a certain strength often causes malicious effects on standard train loss, which decreases accuracy. As shown in Figure 2b and 2c, MaskSub improves the loss convergence for both losses, original and masking, which brings an improvement in accuracy.

Figure 2d explains the learning pattern between main-branch and sub-branch of MaskSub (Eq. (3)) in the aspect of gradients magnitude for training with random masking 50%. The gradient magnitude from the main-branch (MaskSub-Main) is similar to that of other training. In contrast, gradients from the sub-branch (MaskSub-Sub) have a small magnitude at the early stage. As the learning progresses, the gradients from the sub-branch increase. It shows that MaskSub trains the network following our intention: automatic difficulty control. During the early stage of training, the gradients from the main-branch lead the training. Following the progress of the main-branch training, the sub-branch adaptively increases its gradient magnitude and produces a reasonable amount of gradients at the end of training. In other words, the model training is relaxed from challenging masked inputs at the early stage, while it starts to learn masked input when the original inputs are sufficiently trained. We claim that the automatic difficulty control of MaskSub could be a general solution to introduce strong augmentation for supervised learning.

3.3. Expand to drop regularizations

We design MaskSub for masking augmentation. Due to its simplicity, it can be expanded to drop-based regularizations [11, 19, 35]. In this section, we introduce two variants of MaskSub: DropSub for dropout [35] and PathSub for drop-path [19]. Since the drop-based regularizations easily adjust their strength by controlling drop probability, MaskSub enables the model to learn dropped features without degrading performance at a standard loss, similar to masking augmentation. The performance of MaskSub variants is shown in Section 4.8. Note that detailed experiments with loss convergence for various drop rates are reported in Table A.5 in the Appendix.

DropSub. Dropout [35] is a fundamental drop regularization. Dropout drops random elements of network features with a fixed probability. Since dropout is unrelated to feature structure, every feature element has independent drop probability p_{drop}. DropSub is simply implemented by changing r_{mask} to the dropout probability p_{drop}. Thus, the sub-branch uses strong dropout, while the main-branch follows a standard training recipe. Due to stability issues, dropout is not preferred in recent training recipes [36, 37]. However, DropSub enables strong dropout in ViT training and achieves performance improvement.

PathSub. Drop-path [10, 19] randomly drops a total feature of the network block with a probability p_{path}. PathSub is also implemented by changing r_{mask} to the drop-path probability p_{path}. Drop-path widely used in training recipes [36, 37, 44] to adjust the regularization strength [37]. Thus, unlike previous cases, the main-branch uses the drop-path following the training recipe, and the sub-branch uses a higher drop probability than the main-branch.

4. Experiments

We validate the effectiveness of our Masked Sub-branch (MaskSub) by applying it to diverse training scenarios. We claim MaskSub is an easy plug-in solution for various training recipes. Thus, we strictly follow the original training recipe, including optimizer parameters, learning rate and weight-decay, and regularization parameters. The only difference between baseline and MaskSub is the masking augmentation for the sub-branch. We simply set the masking ratio of MaskSub to 50% across all experiments. In short, MaskSub does not have a hyper-parameter that varies depending on training scenarios.

4.1. Training from scratch (pretraining)

The training recipe in ViTs is a key factor enabling ViT to surpass CNN; thus, the ViT training recipe is an important and active research topic. We use a state-of-the-art ViT training recipe, DeiT-III [37], as our baseline. Enhancing DeiT-III by integrating additional techniques is challenging, so we believe improvements made over DeiT-III would represent a new state-of-the-art in ViT training.

Network	400 epochs		800 epochs	
	DeiT-III	+ MaskSub	DeiT-III	+ MaskSub
ViT-S/16	80.4	**81.1** (+0.7)	81.4	**81.7** (+0.3)
ViT-B/16	83.5	**84.1** (+0.6)	83.8	**84.2** (+0.4)
ViT-L/16	84.5	**85.2** (+0.7)	84.9	**85.3** (+0.4)
ViT-H/14	85.1	**85.7** (+0.6)	85.2	**85.7** (+0.5)

Table 1. **Training from scratch with ViT using the DeiT-III.** MaskSub (50%) is applied to the ViT training [37] on ImageNet-1k. Note that the training settings are identical to the original ones.

Network	Method	Epochs	Top-1 acc.	Cost
ViT-S	DeiT [36]	300	79.8	-
	MAE [15]†	1600	81.4	-
	DeiT-III [37]	800	81.4	×1.0
	CoSub [38]	800	81.5	×2.0
	MaskSub	400	81.1	**×0.75**
	MaskSub	800	**81.7**	×1.5
ViT-B	DeiT [36]	300	81.8	-
	MAE [15]	1600	83.6	-
	SupMAE [26]	400	83.6	-
	DeiT-III [37]	800	83.8	×1.0
	CoSub [38]	800	**84.2**	×2.0
	MaskSub	400	84.1	**×0.75**
	MaskSub	800	**84.2**	×1.5
ViT-L	DeiT-III [37]	800	84.9	×1.0
	CoSub [38]	800	**85.3**	×2.0
	MaskSub	400	85.2	**×0.75**
	MaskSub	800	**85.3**	×1.5
ViT-H	DeiT-III [37]	800	85.2	×1.0
	CoSub [38]	800	**85.7**	×2.0
	MaskSub	400	**85.7**	**×0.75**

Table 2. **Pre-training methods comparison.** We compare DeiT-III [37] + MaskSub with various pre-training methods. MaskSub shows remarkable performances compared to its training cost.

	Epochs	Network	Baseline	+MaskSub
MAE [15] finetuning	100	ViT-B/16	83.6	**83.9** (+0.3)
	50	ViT-L/16	85.9	**86.1** (+0.2)
	50	ViT-H/14	86.9	**87.2** (+0.3)
BEiTv2 [30] finetuning	100	ViT-B/16	85.5	**85.6** (+0.1)
	50	ViT-L/16	87.3	**87.4** (+0.1)
CLIP [33] finetuning	50	ViT-B/16	84.8	**85.2** (+0.4)
	30	ViT-L/14	87.5	**87.8** (+0.3)

Table 3. **ImageNet-1k finetuning.** We report finetuning performance of MAE [15], BEiT v2 [30] and CLIP finetuning [8] with MaskSub (50%). Official weights are used.

ViTs are trained with MaskSub (50%) on 400 and 800 epochs training. The results are shown in Table 1. MaskSub improves performance across all settings. For 400-epochs training, MaskSub improves DeiT-III with substantial margins, which even outperforms 800-epochs trained DeiT-III except for ViT-S/16. MaskSub also demonstrates superior performance when training for 800 epochs. The impact of MaskSub is impressively consistent with larger models like ViT-L/16 and ViT-H/16. It is worth noting that ViT-H + MaskSub (400 epochs) outperforms ViT-H/16 (800 epochs) with +0.5pp gain, even with half the training epochs. Thus, MaskSub is an effective way to improve ViT training.

Table 2 shows the performance and computation cost of MaskSub compared to other pretrainings. In ViT-S and ViT-B, MaskSub outperforms MAE [15] with a reasonable performance gap. Compared to SupMAE [26], MaskSup outperforms under the same epochs. CoSub [38] has comparable performance with MaskSub; however, MaskSub requires less computation costs than CoSub. Thus, we argue that MaskSub outperforms CoSub. More comparisons with CoSub are included in Section 4.5.

4.2. Finetuning

Following the emergence of self-supervised learning [15] and visual-language modeling [33], the significance of finetuning has notably increased. Generally, self-supervised learning, such as MAE [15] and BEiT [1, 30], does not use supervised labels at pretraining, which makes MaskSub inapplicable for pretraining. However, a standard is to evaluate the model's capability using supervised finetuning after pretraining. Thus, we apply our MaskSub (50%) to the finetuning stage to verify the effect of MaskSub on finetuning. Note that we strictly follow the original recipes mentioned below and apply MaskSub (50%) based on it. All finetuning is conducted using officially released pretrained weights.

We utilize three finetuning recipes: MAE [15], BEiT

Network	Method	Top-1 acc.
CLIP-B	Linear probing [33]	80.2
	Finetuning [8]	84.8
	Finetuning [8] + MaskSub	**85.2**
ViT-B	FD-CLIP [43]	84.9
	MaskDistill [31]	85.5
	MVP [42]	84.4
	MILAN [18]	85.4
	CAEv2 [54]	85.5
	BEiTv2 [30]	85.5
	BEiTv2 [30] + MaskSub	**85.6**

Table 4. **Comparison with CLIP-based training on ImageNet-1k.** Our finetuning experiment is close to the state-of-the-art of ViT-B training. MaskSub applied to BEiTv2 [30] fine-tuning outperforms cutting-edge studies on CLIP-based training.

v2 [30], and Finetune CLIP [8]. MAE [15] is a representative method of masked image models (MIM). Since our random masking is motivated by MAE, MaskSub is seamlessly integrated into the MAE finetuning process. BEiT v2 [30] utilizes the pretrained CLIP for MIM and achieves superior performance compared to MAE. Following the masking strategy of BEiT v2 using mask-token, we adjust MaskSub to masking using mask-token from the pretrained weight instead of MAE-style masking. Finetune CLIP [8] is a finetuning recipe for CLIP [33] pretrained weights. MaskSub is applied to finetuning CLIP without change.

Table 3 shows the finetuning results. MaskSub improves the performance of all finetune practices, including large-scale ViT models. This is notable as it shows substantial improvement with a short finetuning phase of fewer than 100 epochs compared to the pretraining period of 1600 epochs. In MAE finetuning, MaskSub improves 0.2 - 0.3pp in all model sizes. MaskSub is also effective on BEiT v2, which utilizes Relative Position Encoding (RPE) [1, 27] and block-masking strategy with mask-tokens. CLIP finetuning also displays that MaskSub achieves substantial improvements. In finetuning CLIP, we report performance at the last epoch rather than selecting the best performance in early epochs. The best performance of finetuning CLIP with MaskSub is the same as the baseline. Table 4 demonstrates the impacts of MaskSub compared to cutting-edge CLIP-based training recipes. It shows that MaskSub improves the performance of state-of-the-art training recipes.

4.3. Hierarchical architecture

We extend experiments to architectures with hierarchical spatial dimensions: ResNet [13] and Swin Transformer [27]. Unlike ViT, which maintains spatial token length for all layers, those networks change the spatial size of features in the middle of layers, requiring a change in masking strategy. We apply MaskSub (50%) to ResNet and

Recipe	Epochs	Network	Baseline	+ MaskSub
RSB A2 [44]	300	ResNet50	79.7	**80.0** (+0.3)
		ResNet101	81.4	**82.1** (+0.7)
		ResNet152	81.8	**82.8** (+1.0)
Swin [27]	300	Swin-T	81.3	**81.4** (+0.1)
		Swin-S	83.0	**83.4** (+0.4)
		Swin-B	83.5	**83.9** (+0.4)

Table 5. **ImageNet-1k with hierarchical architecture.** We show the performance of ResNet [13] and Swin Transformer [27] trained from scratch with MaskSub (50%).

Network	Method	Top-1 acc.
ResNet50	Baseline [14]	76.1
	ResNeXt50 [48] + ONE [58]	78.2
	BYOT [52]	75.2
	Self-Distillation [53]	78.3
	MixSKD [49]	78.8
	RSB [44] + MaskSub	**80.0**
ResNet101	Baseline [14]	77.4
	Self-Distillation [53]	78.9
	RSB [44] + SD-dropout [25]	81.2
	RSB [44] + PS-KD [21]	81.7
	RSB [44] + MaskSub	**82.1**
ResNet152	Baseline [14]	78.3
	PS-KD [21]	79.2
	Self-Distillation [53]	80.6
	SD-dropout [25]	75.5
	RSB [44] + SD-dropout [25]	81.8
	RSB [44] + PS-KD [21]	82.3
	RSB [44] + MaskSub	**82.8**

Table 6. **Comparison with self-distillation methods.** Based on ResNet, we compare MaskSub with self-distillation methods.

Swin Transformer. We simply fill out masked regions with zero pixels for ResNets and replace masked regions with mask-tokens for Swin Transformer. It maintains the spatial structure and enables spatial size reduction of hierarchical architecture. Following the literature [45], we use random masking with the patch size of 32×32. Note that the computation reduction in MAE-style masking does not apply here; therefore, MaskSub costs double the training budget. For ResNet, we use an effective training recipe [44] with 300 epochs. The recipe in the original paper [27] is used for the Swin Transformer training. We strictly follow the training recipes and apply MaskSub without tuning them.

Results are shown in Table 5. MaskSub achieves impressive performance gains with ResNet and Swin Transformer as well. ResNet and Swin are substantially different architectures from ViT. Thus, the result implies that the effectiveness of MaskSub is not limited to ViT architectures and is applicable to hierarchical architectures.

Model	Pretraining + MaskSub	Finetuning + MaskSub	CIFAR100 [24]	CIFAR100 [24]	Flowers [29]	Cars [23]	iNat-18 [39]	iNat-19 [39]
ViT-S/16	-	-	98.8	90.0	94.5	80.9	70.1	76.7
	✔	-	**98.9**	**90.6**	95.2	81.2	70.8	77.0
	✔	✔	98.8	89.9	**98.3**	**92.2**	**71.2**	**77.1**
ViT-B/16	-	-	99.1	91.7	97.5	90.0	73.2	78.5
	✔	-	**99.2**	**91.9**	97.7	90.2	73.6	78.8
	✔	✔	98.8	89.6	**98.7**	**92.8**	**73.9**	**79.1**

Table 7. **Transfer learning.** Table shows transfer learning performance with/without MaskSub. We measure the performance when MaskSub is applied to pretraining and finetuning. The standard deviations over three runs are reported in Appendix.

Architecture	+MaskSub	Epochs	GPU days	Accuracy
ViT-S/16	-	600	22	80.7
	✔	400	22	**81.2** (+0.5)
ViT-B/16	-	600	26	83.7
	✔	400	25	**84.1** (+0.4)
ResNet101	-	600	24	81.5
	✔	300	20	**82.1** (+0.6)
ResNet152	-	600	32	82.0
	✔	300	29	**82.8** (+0.8)

Table 8. **Comparison in the same training budget.** Training has been conducted with NVIDIA V100 8 GPUs. GPU days refer to the number of days required for training when using a V100 GPU.

Method	Accuracy	GPU days
Baseline [37]	83.5	17.3
DataAug [17]	83.5 (+0.0)	36.8 (+113%)
GradAug [50]	83.2 (-0.3)	39.7 (+129%)
CoSub [38]	83.9 (+0.4)	35.3 (+104%)
MaskSub	**84.1**(+0.6)	**25.1** (+45%)

Table 9. **ImageNet-1k Comparison.** The table shows performance and computational costs for ViT-B's 400 epoch training.

	Single-scale mIoU		Multi-scale mIoU	
	DeiT-III	+ MaskSub	DeiT-III	+ MaskSub
ViT-B	48.8	**49.4** (+0.6)	49.7	**50.2** (+0.5)
ViT-L	51.7	**52.2** (+0.5)	52.3	**52.7** (+0.4)

Table 10. **Semantic segmentation on ADE-20k.** UpperNet for ViT backbone is trained with the BEiTv2 segmentation recipe.

4.4. Self-distillation

We compare MaskSub with self-distillation methods. As shown in Table 6, most self-distillations report their performance based on weak and old recipes. Thus, they are less effective with cutting-edge recipes (RSB [44]) or architectures (ViT). Otherwise, MaskSub can be plugged into strong training recipes and achieves state-of-the-art with self-distillation loss. Thus, MaskSub has contributed to practical self-distillation with its broad applicability.

4.5. Training budget

We have shown that MaskSub effectively improves the performance of various architectures. However, MaskSub requires additional computation costs for the sub-branch, which increases training costs. Thus, we analyze MaskSub regarding its training costs to determine if MaskSub could be an effective solution within a limited training budget. We compare MaskSub with training recipes with increased epochs to align with the training budget. The training budget is quantified regarding required GPU days when only a single NVIDIA V100 GPU is used for training. Table 8 shows the results. In ViT training, MaskSub outperforms baseline with $\times 1.5$ epochs setting. Thus, MaskSub is superior to the long epoch training to spend computation costs for training ViT. For ResNet, we compare 300 epochs MaskSub with 600 epochs training recipe RSB [44] A1. MaskSub outperforms 600 epochs training recipes in ResNet101 and ResNet152. Consequently, the results show that MaskSub is an effective way to improve training, even considering computation costs for the sub-branch.

We compare MaskSub with other training methods: DataAugment [17], GradAug [50], and CoSub [38]. DataAugment [17] uses doubled data augmentations for the same image, which is similar to contrastive learning [2, 4]. GradAug [50] utilizes a network pruning [51] to build sub-network. CoSub introduces a sub-network based on drop-path [19] and uses the sub-network as mutual learning [55]. Table 9 shows the 400-epochs training from scratch result. Note that GradAug in Table 9 is a 200-epochs training result to adjust computation cost similar to other methods. All augmentation methods require additional computation costs. In particular, GradAug spends almost 300% of additional training costs compared to original training. On the other hand, our MaskSub only requires a small amount of extra costs (below 50%), which is a remarkable advantage in training. With the smallest computation, our MaskSub achieves substantial performance improvements. MaskSub performs superior to CoSub in all cases.

Model	+MaskSub	MNLI	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	Average
BERT [7]	-	84.1	87.5	91.0	91.6	54.7	**87.0**	88.5	62.8	80.9
base	✔	**84.5**	**87.7**	**91.3**	**91.9**	**58.3**	86.8	**89.2**	**63.2**	**81.6**
BERT [7]	-	86.8	88.2	92.3	93.8	63.3	**89.3**	**92.0**	**69.7**	84.4
large	✔	**87.1**	**89.0**	**92.7**	**94.0**	**65.2**	88.6	91.5	69.3	**84.7**

Table 11. **GLUE [40] benchmark with BERT [7].** We apply MaskSub on GLUE benchmark to validate the effect of MaskSub on language model fine-tuning. MaskSub effectively improves BERT finetuning performance.

Training method	ImageNet-1k Zero-shot acc.
CLIP [33]	33.5
CLIP [33] + Masking	29.8 (-3.7)
CLIP [33] + MaskSub	**37.6** (+4.1)

Table 12. **MaskSub on CLIP pretraining** with ViT-B/32. We apply MaskSub to CLIP, vision and language, pre-training process. MaskSub is effective for CLIP pre-training.

4.6. Transfer learning

Improvement in pretraining can boost the performance of downstream tasks [22]. We measure the transfer learning performance of MaskSub using 800 epochs pretrained weight from Table 1. CIFAR-10 [24], CIFAR-100 [24], Oxford Flowers-102 [29], Stanford Cars [23] and iNaturalist [39] are used for finetuning datasets. We use the AdamW training recipe [37] and also evaluate performance when MaskSub (50%) is applied to the finetuning process. Table 7 shows the results. The backbone pretrained with MaskSub consistently outperforms the DeiT-III backbone across all cases. Moreover, when MaskSub is applied to the finetuning, it further boosts performance except CIFAR [24].

We verify transfer learning to semantic segmentation task on ADE-20k [57]. We train UperNet [46] training recipe [30] and utilize pretrained weight from Table 1. Table 10 shows the segmentation results of single-scale and multi-scale evaluations. On both evaluations, the backbone pretrained with MaskSub demonstrates superior performance, consistent for ViT-B and ViT-L.

4.7. Beyond vision domain

MaskSub can be extended to domains beyond images, as long as the masking is applicable. Thus, we apply MaskSub to two additional tasks beyond the image domain: GLUE [40] benchmark and CLIP [33] pretraining. The first task is a text-classification benchmark GLUE [40]. We use BERT [7] as a pretrained model and apply MaskSub with 15% masking following the masking ratio of BERT. As shown in Table 11, MaskSub improves text-classification performance. MaskSub is also applied to CLIP [33] pretraining. Table 12 shows the results. CLIP trained with MaskSub (50%) shows improved zero-shot performance.

Architecture	Baseline	MaskSub	DropSub	PathSub
ViT-S/16	80.4	**81.1** (+0.7)	80.6 (+0.2)	80.8 (+0.4)
ViT-B/16	83.5	**84.1** (+0.6)	83.8 (+0.3)	83.8 (+0.3)
Computation	×1.0	×1.5	×2.0	×2.0

Table 13. **Comparison of MaskSub variants.** We validate drop-based variants of MaskSub. The sub-branch training improves performance with other drop-methods. But, MaskSub shows the best improvement with the smallest computations.

Experimental details are in Appendix. These results verify that MaskSub has remarkable impacts not only on the vision but also on the language and vision&language domain.

4.8. Extending to drop regularizations

In Section 3.3, we expand MaskSub with drop regularizations [19, 35]. We validate the performance of MaskSub variants on a 400 epochs training with Deit-III. We use masking [15] (50%), dropout [35] (0.2), and drop-path [19] (baseline + 0.1) for MaskSub, DropSub, and PathSub, respectively. Table 13 shows the results. Variants of MaskSub outperform the baseline. Among the three, MaskSub shows the best performance. Also, MaskSub has the lowest computation costs due to MAE [15]-style computation reduction. Thus, we conclude that MaskSub (50%) is the best in practice compared to variants with drop regularizations. Note that Table A.5 in Appendix includes more results.

5. Conclusion

In this work, we have presented a new way to introduce masking augmentation to supervised learning. Our method, Masked Sub-branch (MaskSub), is designed to leverage masking augmentation within a sub-branch, which is separated from main training and uses a relaxed loss function. Our extensive analysis reveals that MaskSub effectively mitigates malicious effects of heavy masking while accelerating the convergence, yielding superior performance. We verify MaskSub on various training recipes with diverse architecture. Notably, MaskSub demonstrates impressive performance improvements across various scenarios. We claim that MaskSub is a substantial advancement in training recipes and contributes to using augmentations.

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