



MixPro: Data Augmentation with MaskMix and Progressive Attention Labeling for Vision Transformer



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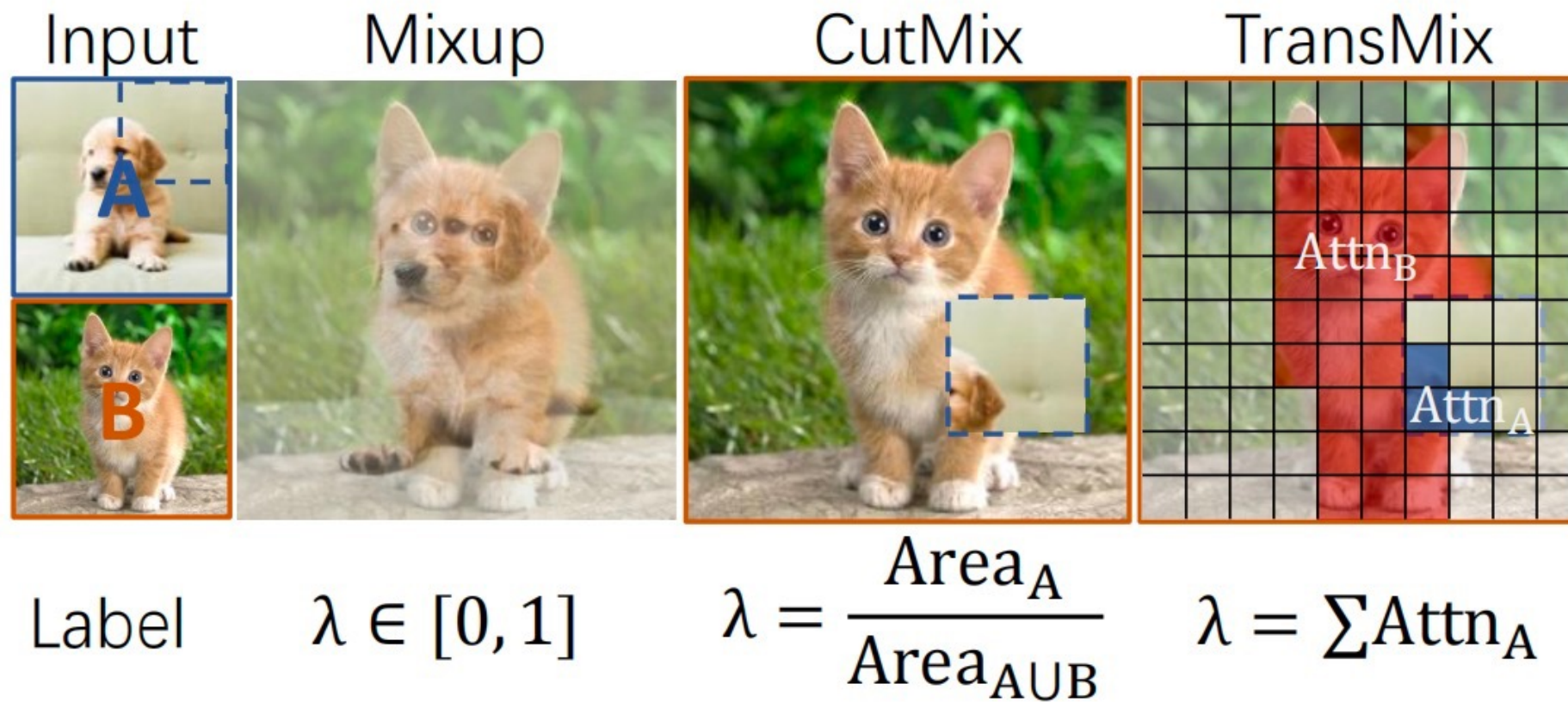
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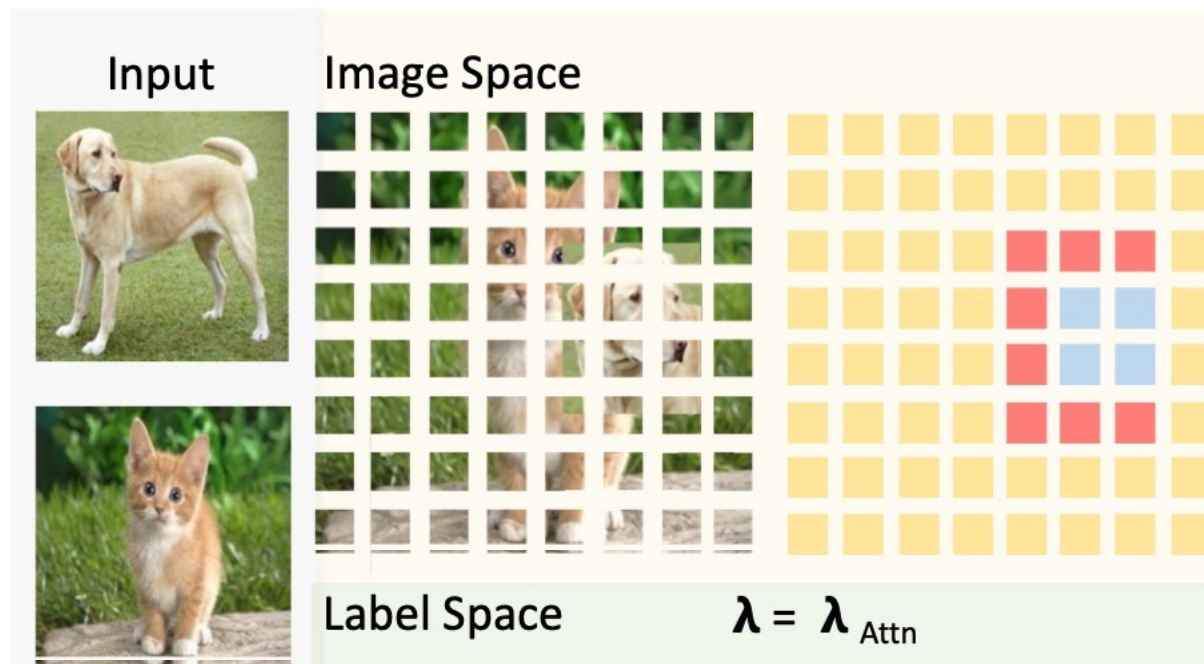


Previous Mixed augmentation methods for Vision Transformer





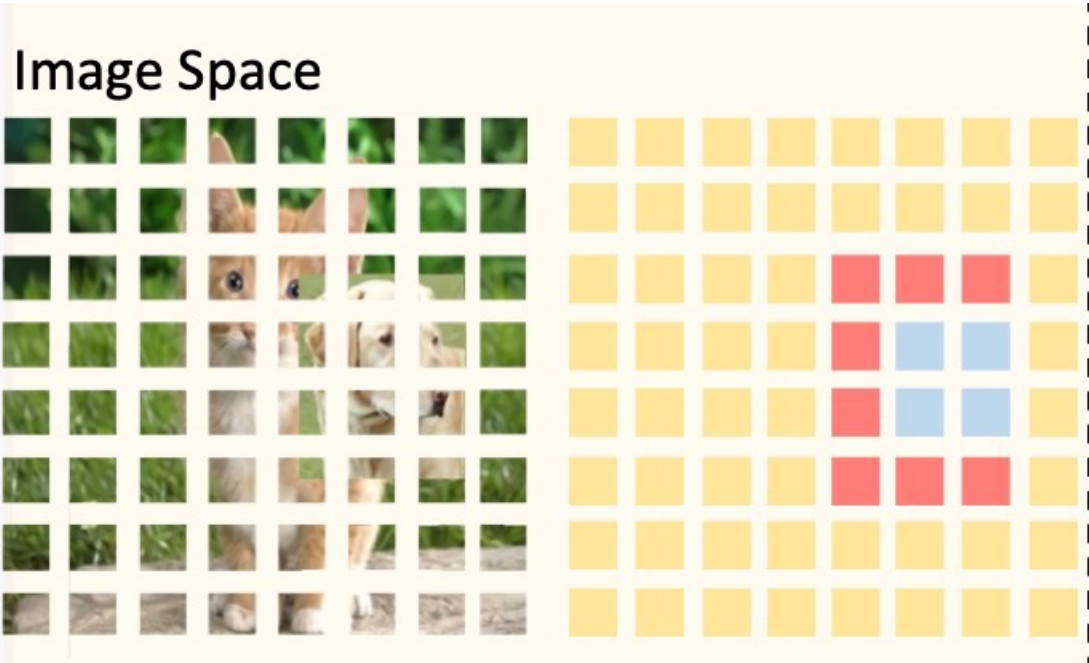
Shortcomings of TransMix



- ViTs has long-range dependence, region-based mixed images may provide insufficient regularization.
- Cropped patches with sharp rectangular borders are clearly distinguishable from the background (viewed as red patches), resulting in a basis weight of attention regardless of whether the patch contains useful information.

Attention maps may not always be reliable during the training process.

- At the beginning of the training, the model has no representation capability, and the attention maps gained are unreliable.
- it is possible to obtain difficult samples using massive data augmentation strategies, and the attention map is also unreliable.



Label Space

$$\lambda = \lambda_{\text{Attn}}$$

(a) TransMix



$$\lambda = \alpha \cdot \lambda_{\text{Attn}} + (1 - \alpha) \cdot \lambda_{\text{area}}$$

(b) MixPro



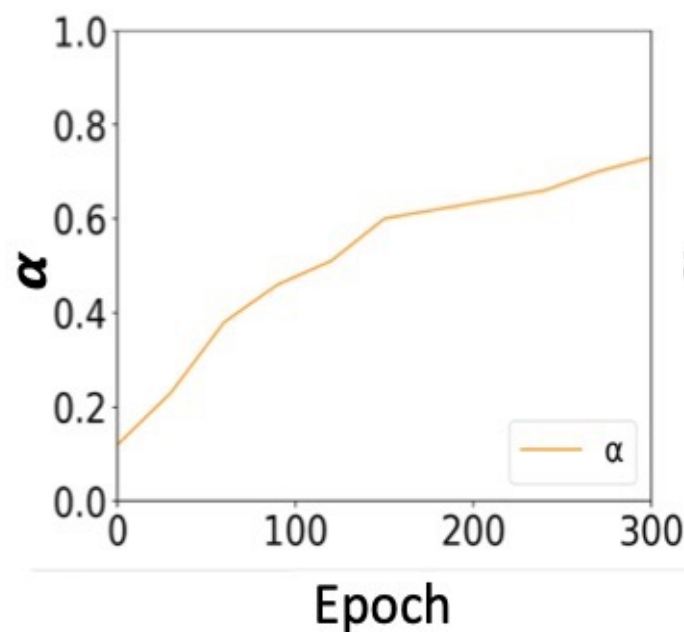
How to get progressive factor α ?

Setp 1

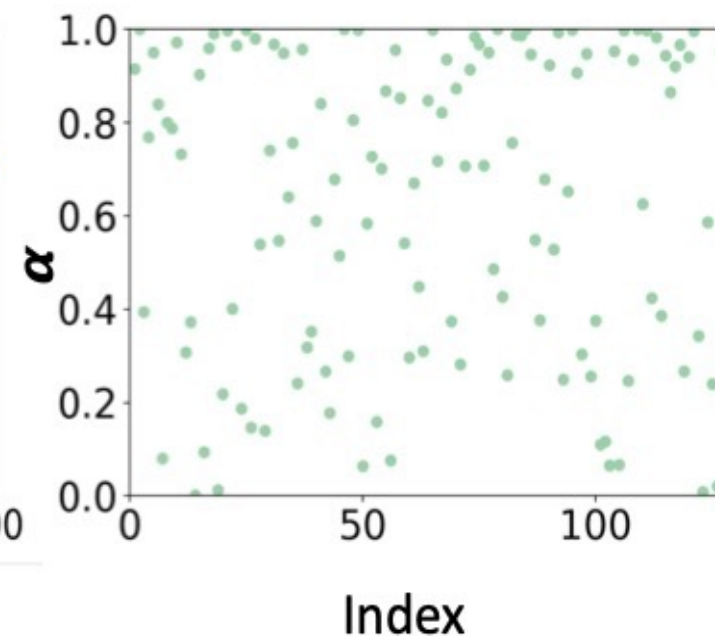
$$\tilde{y} = \lambda_{area} \odot y_i + (\mathbf{1} - \lambda_{area}) \odot y_j$$

Setp 2

$$\alpha = \mathbf{d}(\mathbf{p}, \tilde{\mathbf{y}}) = \frac{\mathbf{p} \cdot \tilde{\mathbf{y}}^\top}{\|\mathbf{p}\| \cdot \|\tilde{\mathbf{y}}\|},$$



(a) Trends of α



(b) α in a mini-batch



Table 1: Compared to TransMix, MixPro provides better performance on a wide range of model variants, e.g. DeiT, PVT, CaiT, XCiT, Swin on ImageNet-1k classification. All the baselines are reported in TransMix (Chen et al., 2021).

Models	Params	#FLOPs	Top-1 Acc(%)	Top-1 Acc(%) +TransMix	Top-1 Acc(%) +MixPro
DeiT-T (Touvron et al., 2021a)	5.7M	1.6G	72.2	72.6	73.8(+1.2)
PVT-T (Wang et al., 2021)	13.2M	1.9G	75.1	75.5	76.7(+1.2)
XCiT-T (Ali et al., 2021)	12M	2.3G	79.4	80.1	81.2(+1.1)
CA-Swin-T (Liu et al., 2021)	28.3M	4.2G	81.6	81.8	82.8(+1.0)
CaiT-XXS	17.3M	3.8G	79.1	79.8	80.6(+0.8)
DeiT-S (Touvron et al., 2021a)	22.1M	4.7G	79.8	80.7	81.3(+0.6)
PVT-S (Wang et al., 2021)	24.5M	3.8G	79.8	80.5	81.2(+0.7)
XCiT-S (Ali et al., 2021)	26M	4.8G	82.0	82.3	82.9(+0.6)
CA-Swin-S (Liu et al., 2021)	49.6M	8.5G	82.8	83.2	83.7(+0.5)
PVT-M (Wang et al., 2021)	44.2M	6.7G	81.2	82.1	82.7(+0.6)
PVT-L (Wang et al., 2021)	61.4M	9.8G	81.7	82.4	82.9(+0.5)
XCiT-M (Ali et al., 2021)	84M	16.2G	82.7	83.4	84.1(+0.7)
DeiT-B (Touvron et al., 2021a)	86.6M	17.6G	81.8	82.4	82.9(+0.5)
XCiT-L (Ali et al., 2021)	189M	36.1G	82.9	83.8	84.7(+0.9)



pretrained	Backbone	Decoder	mIoU	+MS
ResNet101	ResNet101	Deeplabv3+	47.3	48.5
DeiT-S			49.1	49.6
+TransMix	DeiT-S	Linear	49.7	50.3
			50.3	50.9
DeiT-S			49.7	50.5
+TransMix	DeiT-S	Segmenter	50.6	51.2
			51.1	51.6

Semantic Segmentation

Backbone	#Params	Object detection			Instance segmentation		
		AP^b	AP_{50}^b	AP_{75}^b	AP_m	AP_{50}^m	AP_{75}^m
ResNet50	44.2M	38.0	58.6	41.4	34.4	57.1	36.7
ResNet101	63.2M	40.4	61.1	44.2	36.4	57.7	38.8
PVT-S	44.1M	40.4	62.9	43.8	37.8	60.1	40.3
TransMix-PVT-S	44.1M	40.9	63.8	44.0	38.4	60.7	41.3
MixPro-PVT-S	44.1M	41.4	64.2	44.4	38.9	61.1	41.7

Objection detection and Instance Segmentation



- We propose a new data augmentation method, MixPro, to address the shortcomings of TransMix from the perspective of image space and label space, respectively.
- From the perspective of image space, MixPro ensures that each image patch comes from only one image and uses a global mixed mask to provide more regularization. From the perspective of label space, MixPro utilizes a progressive factor to dynamically re-weight the attention weight of the mixed attention label.
- In experiments, we demonstrate extensive evaluations of MixPro on various ViT-based models and downstream tasks. It boosts DeiT-T achieving 73.8% on ImageNet-1K. Furthermore, compared to TransMix, MixPro also shows stronger robustness on three different benchmarks.

Code link: <https://github.com/fistyee/MixPro>

Thank you