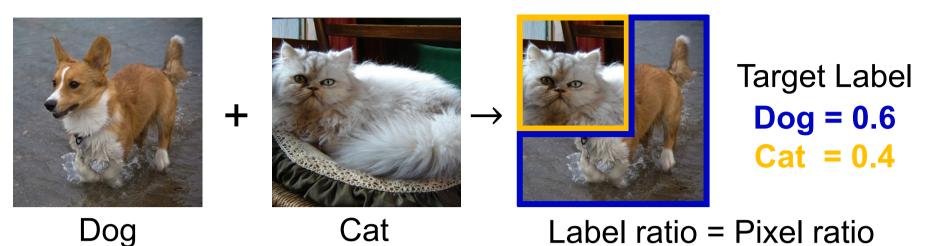
NAVER LINE Clova

CutMix: Regularization Strategy to Train Strong Classifiers with Localizable Features Dongyoon Han¹ Sanghyuk Chun¹ Junsuk Choe² Sangdoo Yun¹ Seong Joon Oh¹ Youngjoon Yoo¹

CutMix in a Nutshell



Q) What is **CutMix**?

- Blend two images and labels by **cut-and-paste** manner.
- Q) What are the benefits of **CutMix**?
 - 1. **Simple**, **intuitive**, and **effective**. (only 20 lines of PyTorch)
 - 2. Vastly improves classifier's accuracy, localization ability.

Motivation and Related Works

- Goal: to learn generalizable and localizable features.
- Comparison with previous works:



Label

Dog 1.0

Dog 1.0

Cat 0.5

Dog 0.6 Cat 0.4

- Unlike Cutout, CutMix uses all input pixels for training.
- Unlike Mixup, CutMix presents realistic local image patches.

[a] Devries et al., "Improved regularization of convolutional neural networks with cutout", arXiv 2017. [b] Zhong et al., "Random erasing data augmentation", arXiv 2017.

[c] Zhang et al., "mixup: Beyond empirical risk minimization.", ICLR 2018.

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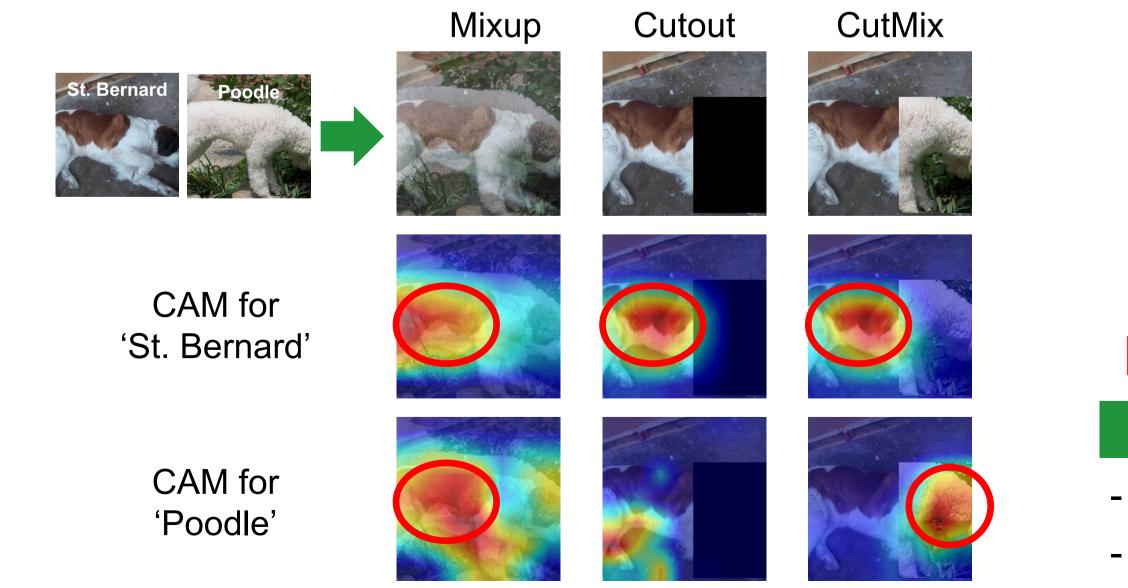
Yonsei University²

Method

- How to training with CutMix:
- 1. For training samples $(x_A, y_A), (x_B, y_B)$ in a minibatch
- 2. Sample mixing ratio $\lambda \sim \text{Unif}(0,1)$
- 3. Select cropping mask M (the cropping area ratio = 1λ)
- 4. CutMix sample is generated by,

$$\tilde{x} = \mathbf{M} \odot x_A + (\mathbf{1} - \mathbf{M}) \odot x_B$$
$$\tilde{y} = \lambda y_A + (1 - \lambda) y_B,$$

- 5. Then, train a classifier using the CutMix sample (\tilde{x}, \tilde{y})
- Classification problem is changed to finding "what", "where", and "how large" the objects in image.



- Our codes and models: github.com/clovaai/CutMix-PyTorch

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Resl Mix

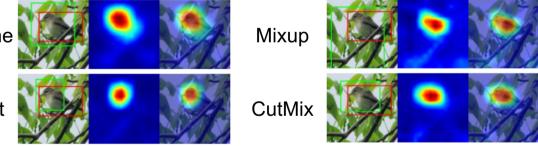
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Experiments

		<image< th=""><th>Net Cla</th><th>ssifica</th><th>ation></th><th></th><th></th><th></th><th></th><th></th></image<>	Net Cla	ssifica	ation>					
odel		Top-1 Acc (%)	Top-5 Acc (%)	(%)			79.8 (+1.6)		80.5 (+1.7)	
esNet-50 (Baseline) esNet-50 + Cutout (ari esNet-50 + StochDepth esNet-50 + Mixup (ICI esNet-50 + DropBlock esNet-50 + Manifold M esNet-50 + AutoAugme	(ECCV'18) LR'18) (NeurIPS'18) lixup (ICML'19)	76.3 77.1 77.5 77.4 78.1 77.5 77.6	93.0 93.3 93.7 93.6 94.0 93.8 93.8	Top-1 accuracy	78.6 (+2.3) 76.3 ResNet-50	78. ⁻ Res	1 Net-101		8.8 sNeXt-101	
esNet-50 + CutMix		78.6	94.1		Base	eline	С	utMix		
<pre>esNet-152 78.3 94.1 </pre>										



PyramidNet-200	Top-1 Acc (%)	Top-5 Acc (%)
Baseline	83.6	96.3
CutMix	85.6	97.0
Center Gaussian CutMix	84.1	96.6
Fixed-size CutMix	85.0	96.9
One-hot CutMix	84.1	96.7
Scheduled CutMix	85.3	96.8
Complete-label CutMix	84.8	96.9

<Transfer Learning with CutMix-pretrained Model>

		•			
ckbone	Pascal VOC Detection		MS-COCO Detection	Image Captioning	
twork	SSD Faster-RCNN		Faster-RCNN	NIC	
IWOIK	(mAP)	(mAP)	(mAP)	(BLEU-4)	
sNet-50 (Baseline)	76.7 (+0.0)	75.6 (+0.0)	33.3 (+0.0)	22.9 (+0.0)	
xup-pretrained	76.6 (-0.1)	73.9 (-1.7)	34.2 (+0.9)	23.2 (+0.3)	
tout-pretrained	76.8 (+0.1)	75.0 (-0.6)	34.3 (+1.0)	24.0 (+1.1)	
tMix-pretrained	77.6 (+0.9)	76.7 (+1.1)	35.2 (+1.9)	24.9 (+2.0)	

Conclusion

- Need a strong classifier? \rightarrow Apply CutMix to your classifier.

Better pretrained model? → Download CutMix-pretrained model.

