Colorful Cutout: Enhancing Image Data Augmentation with Curriculum Learning

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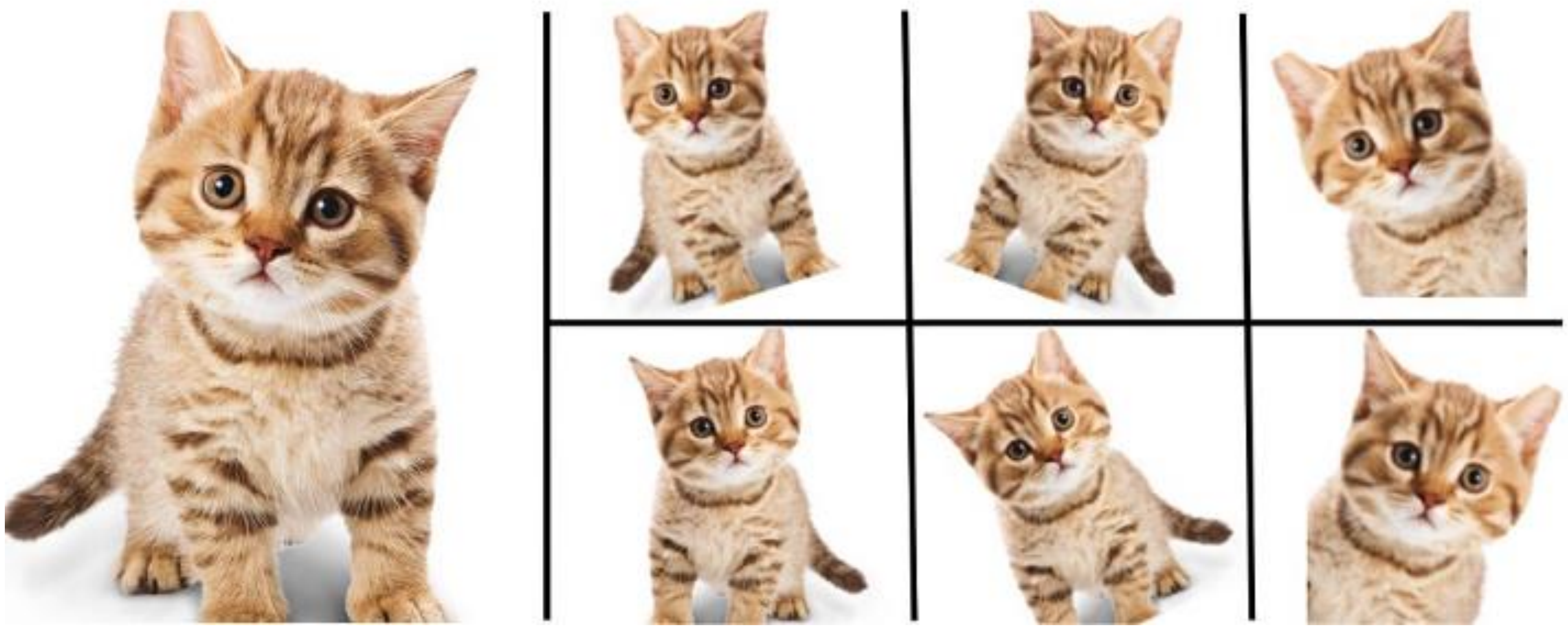
Data Augmentation

In the field of deep learning, **data augmentation** is widely used for regularization

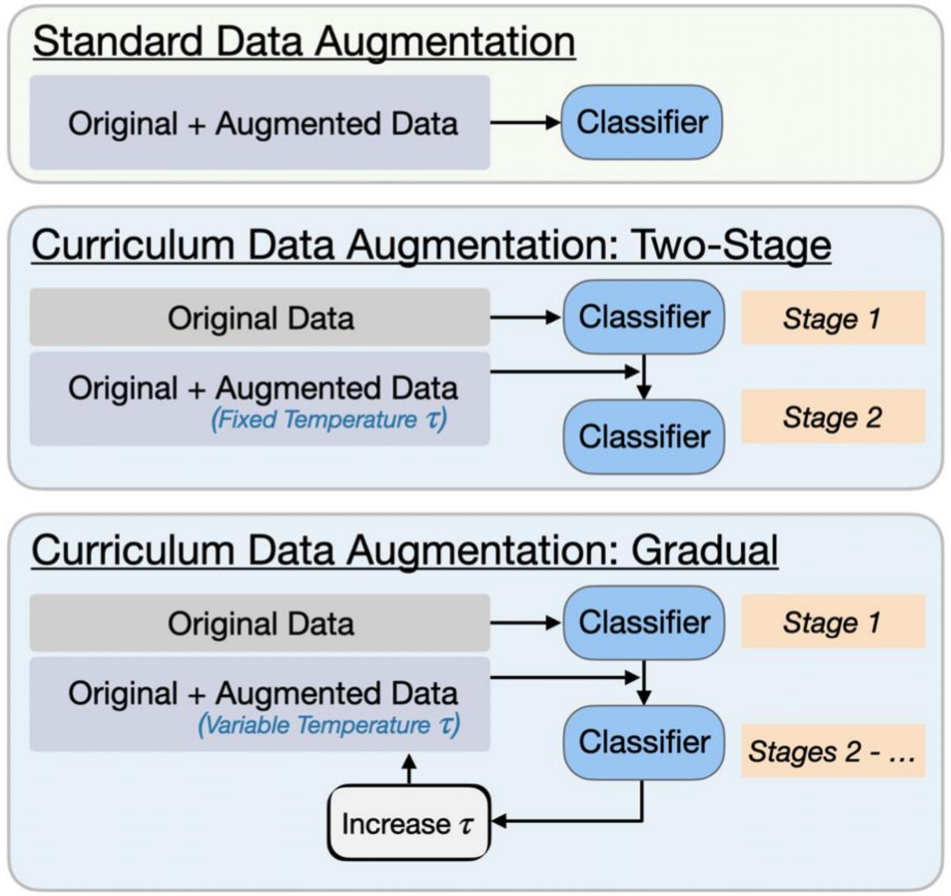
- **Data augmentation** aims to transform given data to enlarge the training dataset
- For instance, we can augment an image by rotating or flipping it
- Data augmentation enhances the performance and generalizability of the model

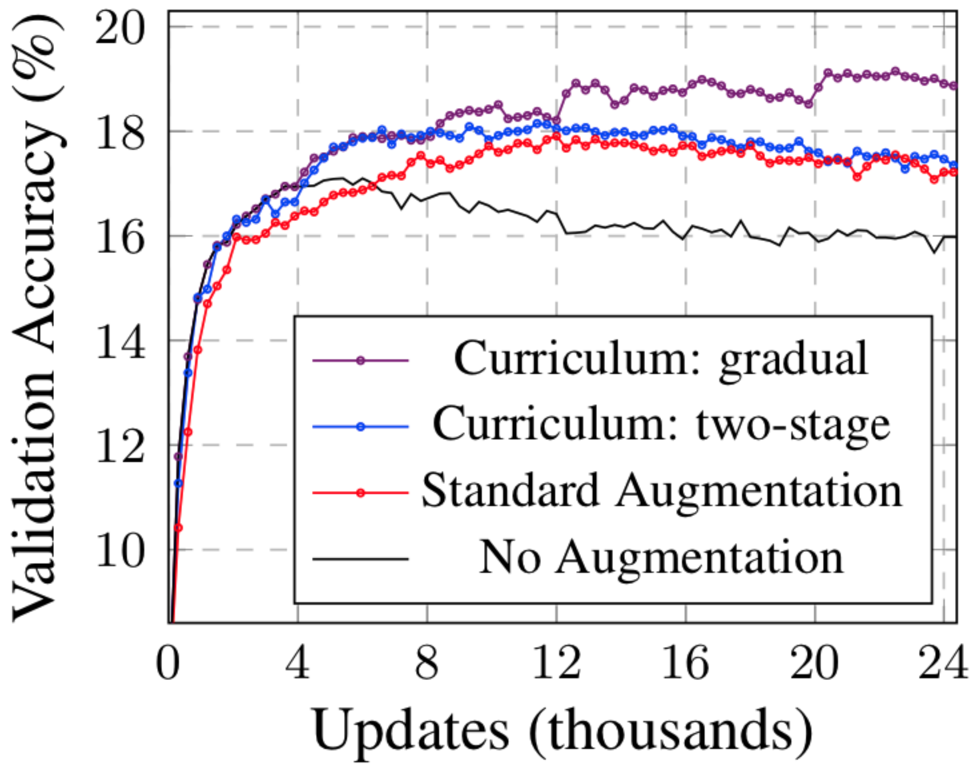


Curriculum Data Augmentation

Recently, reserachers suggested to incorporate curriculum learning and data augmentation

- **Curriculum data augmentation** aims to sequentially enhance the difficulty of augmented data
- For instance, a previous study[1] gradually increased the amount of modification for data augmentation
- They found this approach can improve conventional data augmentation



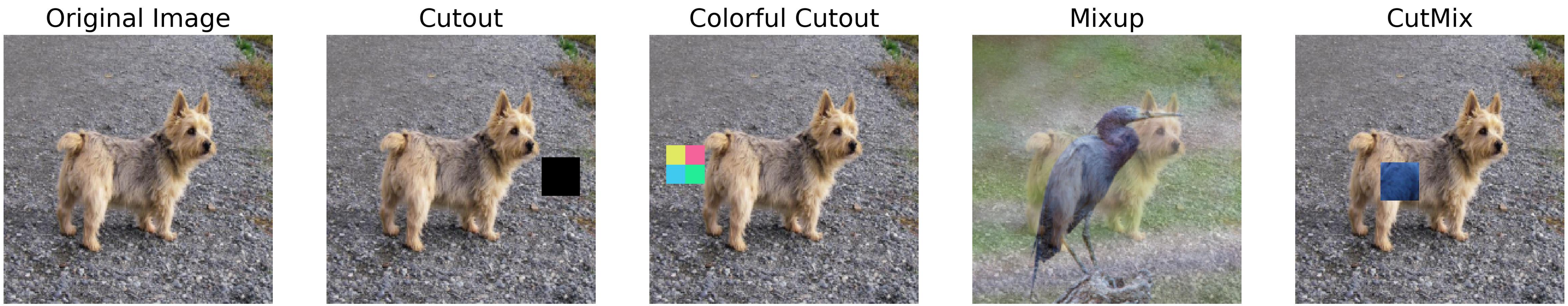


1. Wei et al., *Few-Shot Text Classification with Triplet Networks, Data Augmentation, and Curriculum Learning*, NAACL 2021

Our Motivation

While curriculum data augmentation is promising, it is primarily applied for text data

- We explore the method for **curriculum data augmentation for image data**
- We achieve this through straightforward modification of Cutout[1], while maintaining its simplicity

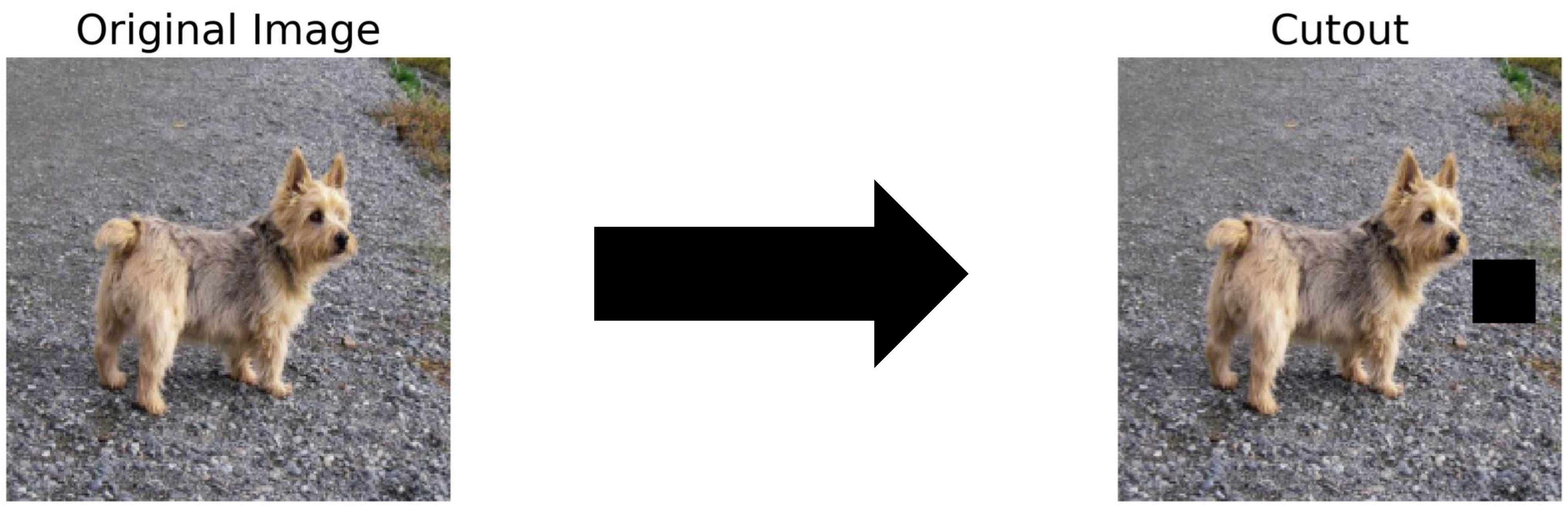


1. DeVries and Taylor, *Improved Regularization of Convolutional Neural Networks with Cutout*, arXiv Preprint 2017.

Preliminary: Cutout

Cutout introduces augmentation by randomly masking out a box region of given image

- For a given image x, augmented image $\hat{x}$ is generated by masking box region
- In general, the box is filled with zero value
- This simple method introduces variation and improves performance of the model

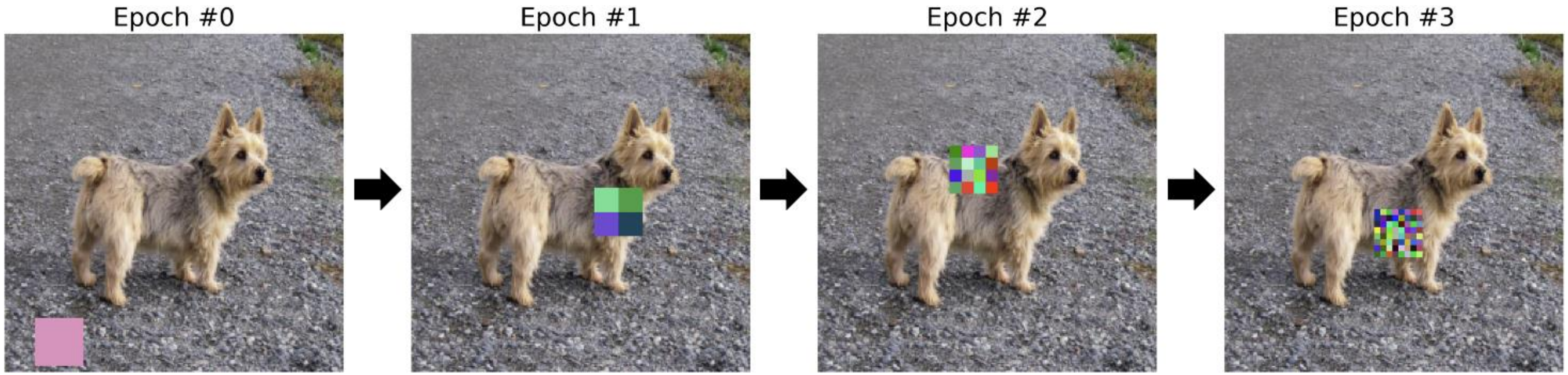


Proposed Method: Colorful Cutout

We propose **colorful cutout** with several updates to previous cutout:

1. We fill the mask box with random color, instead of zero value
2. We divide the mask box into sub-region and fill each region with different colors
3. We increase the number of sub-region as the epoch increases: $2^{N_{epoch}}$

- This configuration enables curriculum data augmentation,
  as it introduces more complex, thus difficult noises



Experimental Result

We performed our experiment on three different models and datasets, with various baselines

- Models: ResNet50, EfficientNet-B0, ViT-B/16
- Datasets: CIFAR-10, CIFAR-100, Tiny ImageNet
- Baselines: Cutout, Mixup, Cutmix
- We found our method exhibits remarkable performance improvement
- The ablation study that excludes curriculum reveals its importance

	ResNet50			**EfficientNet-B0**			**ViT-B/16**		
Dataset	C10	C100	TI	C10	C100	TI	C10	C100	TI
Baseline	94.82	80.56	73.09	96.48	82.38	78.25	95.58	83.94	81.54
Cutout	95.49	80.97	73.52	96.56	82.53	78.41	96.08	84.21	81.49
Mixup	95.56	81.15	73.24	96.63	82.50	78.26	96.45	84.25	81.48
CutMix	95.67	81.45	73.63	96.67	82.96	78.53	96.27	84.32	81.82
Ours w/o Curr.	95.16	81.15	73.61	96.72	82.92	78.32	96.35	84.20	82.15
Ours	**95.70**	**81.57**	**73.81**	**96.81**	**83.37**	**78.65**	**96.55**	**84.36**	**82.36**

Conclusion

We proposed:

- **Colorful cutout**, a simple method for curriculum data augmentation for image data

We found that:

- Our colorful cutout demonstrates effectiveness compared to previous methods
- The inclusion of curriculum is important for colorful cutout, suggesting its strength

We plan to:

- Expand our approach to other image augmentation techniques
- Develop a dedicated approach for curriculum data augmentation for image data

Thank You!