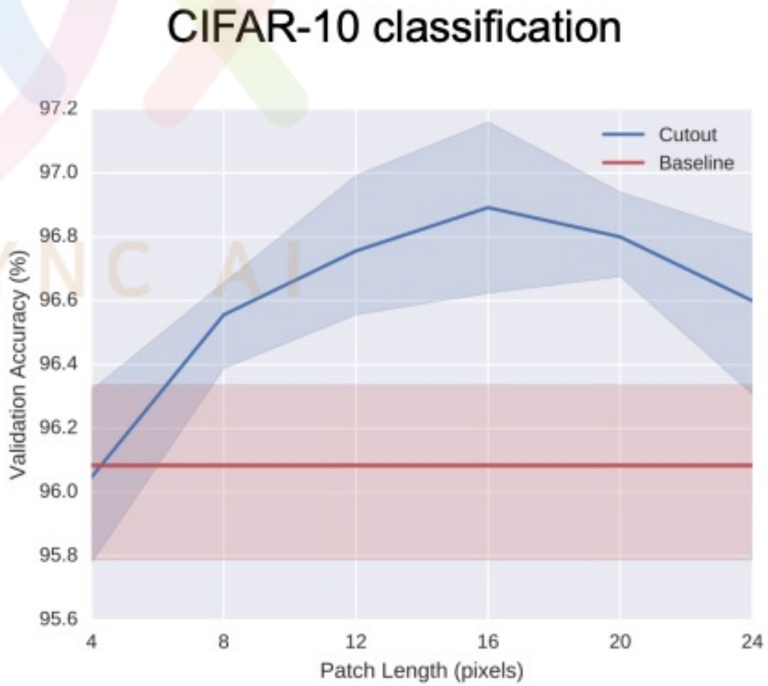
심화 교육과정

Data Augmentation for Computer Vision

Data Augmentation for Computer Vision

Cutout – DeVries and Taylor, 2017

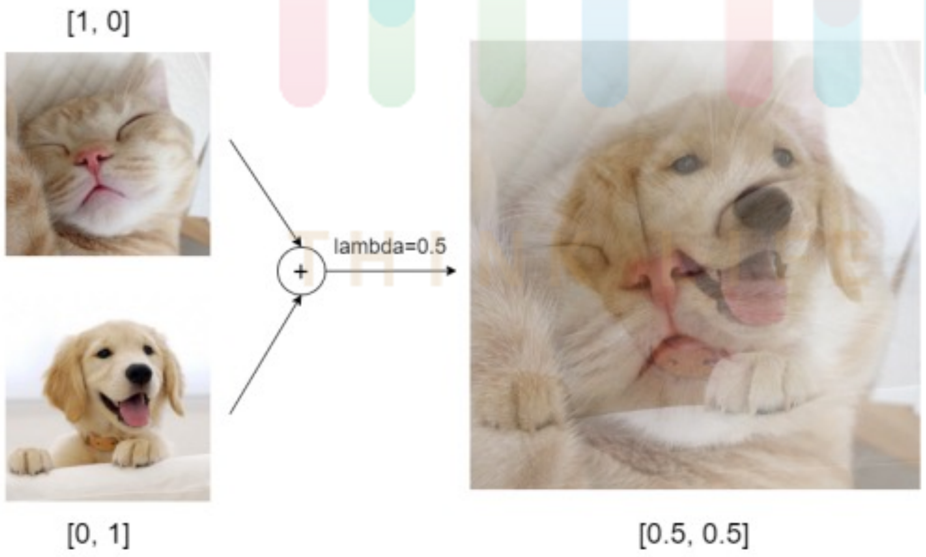
Randomly replace square patches with noise
- 사각 패치를 랜덤한 위치에 두는 방법
- 이 논문에서는 모델의 훈련과정 동안 입력 이미지에서 무작위로 정사각형 영역을 가리는 단순한 방법

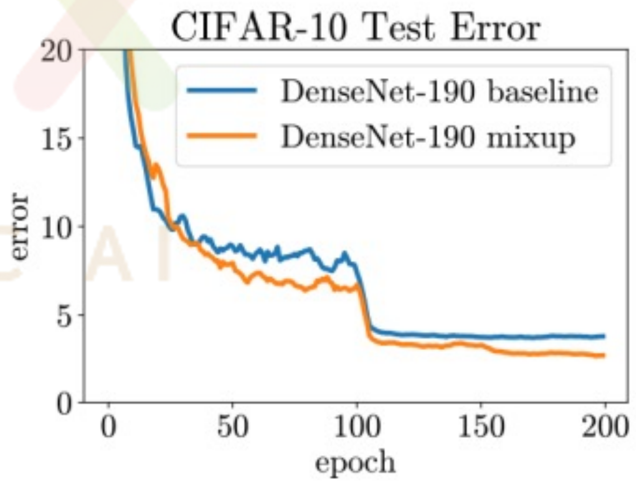


논문 링크 -> https://arxiv.org/abs/1708.04552

Mixup Zhang et al., 2018

Convex combination of pairs of images and their class labels





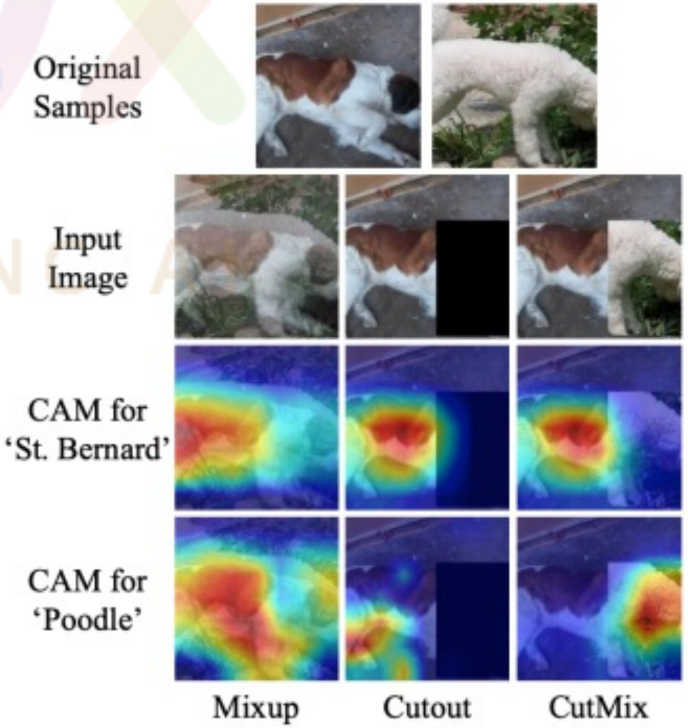
(b) Test error evolution for the best ERM and *mixup* models.

논문 주소 : https://arxiv.org/abs/1710.09412v2

CutMix Yun et al., 2019

Patches are cut and pasted among training images
Class labels are also mixed proportionally to the area of the patches.

	ResNet-50	Mixup [48]	Cutout [3]	CutMix
Image				
Label	Dog 1.0	Dog 0.5 Cat 0.5	Dog 1.0	Dog 0.6 Cat 0.4
ImageNet Cls (%)	76.3 (+0.0)	77.4 (+1.1)	77.1 (+0.8)	**78.6 (+2.3)**
ImageNet Loc (%)	46.3 (+0.0)	45.8 (-0.5)	46.7 (+0.4)	**47.3 (+1.0)**
Pascal VOC Det (mAP)	75.6 (+0.0)	73.9 (-1.7)	75.1 (-0.5)	**76.7 (+1.1)**

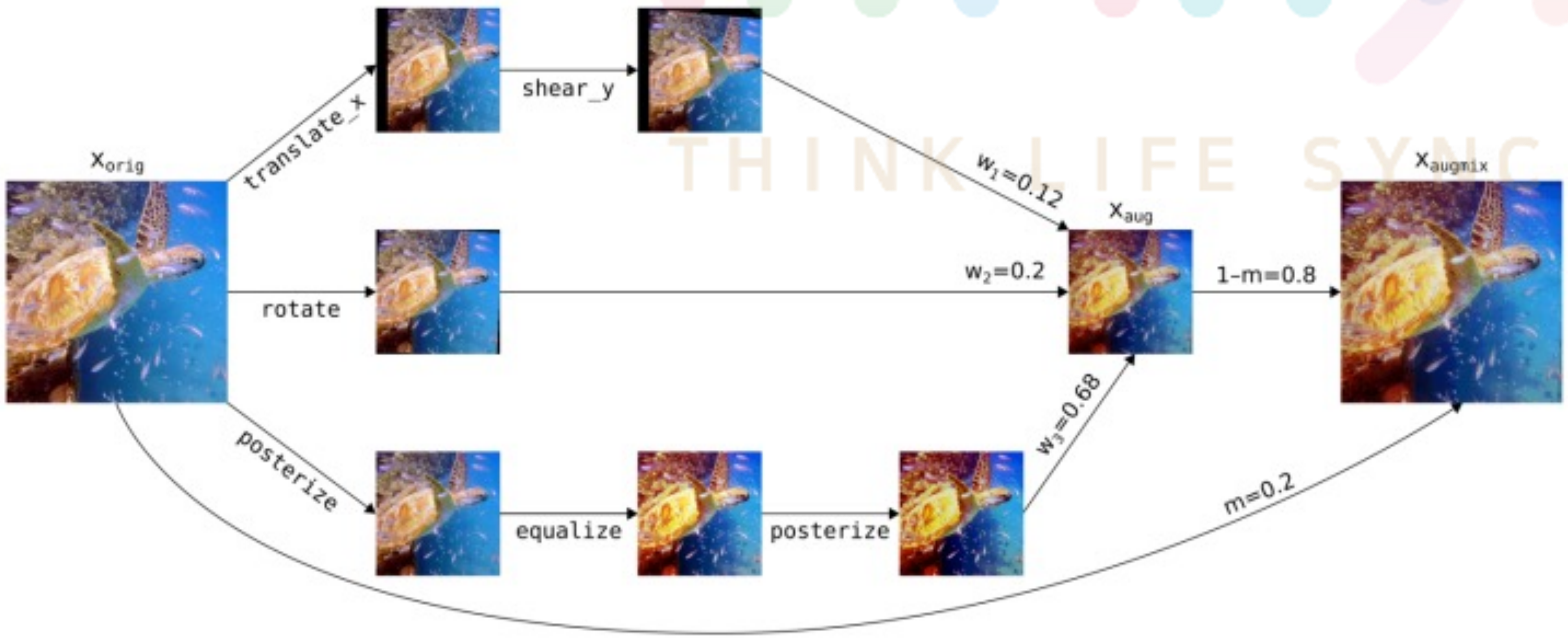


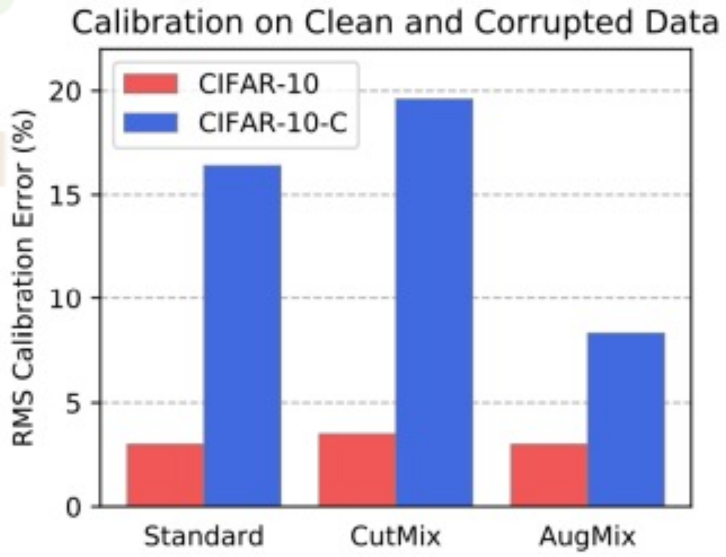
논문 주소 : https://arxiv.org/abs/1905.04899

Infinyx

AugMix Hendrycks et al., 2019

Create multiple augmented images and mix them
Augmentation operations and the mixing weights are randomly sampled
Improves noise robustness and uncertainty estimates.

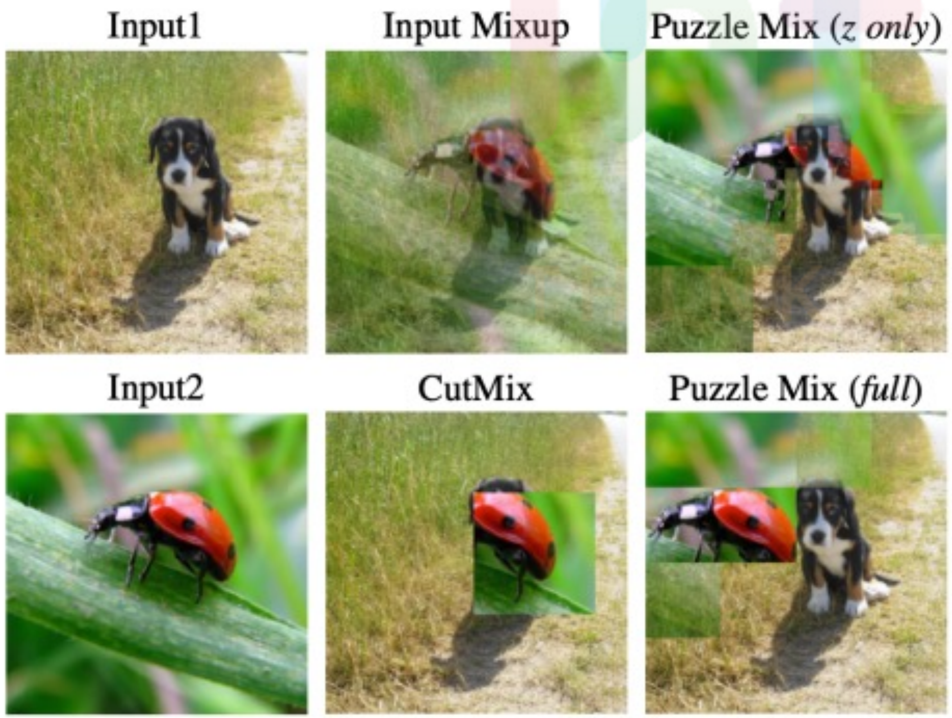


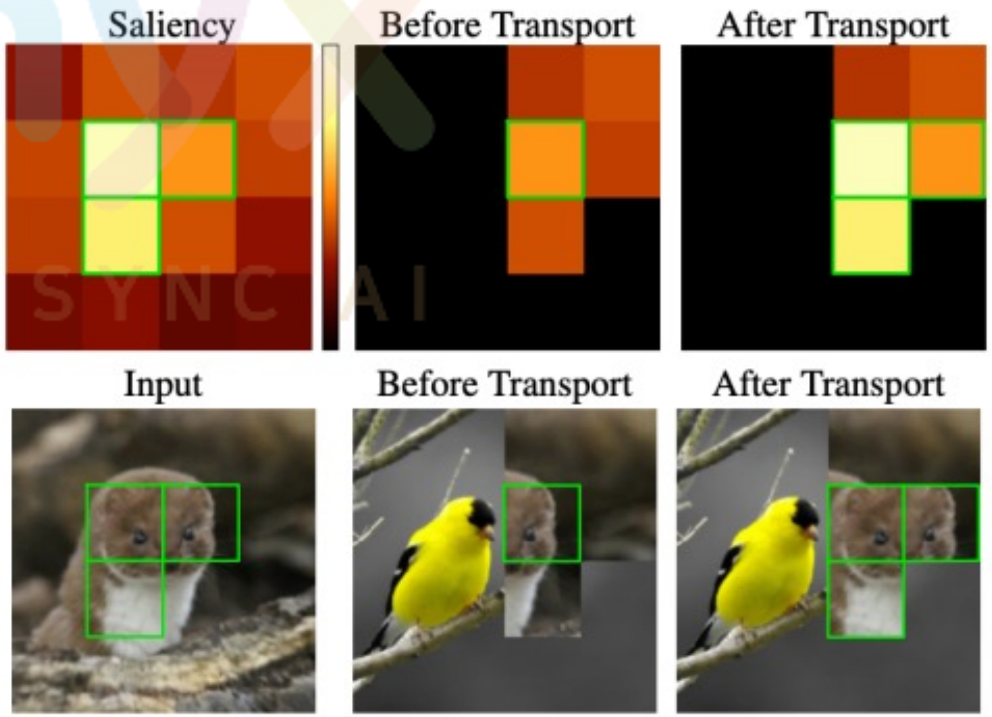


논문 주소 : https://arxiv.org/abs/1912.02781

Puzzle Mix Kim et al., 2020

Utilize the regional saliency information of natural images.
Solve an binary transport problem to find the optimal move that maximizes saliency.





최적화 문제를 기반하여 Cutmix 기법을 업그레이드한 데이터 증강 기법. https://arxiv.org/abs/2009.06962

AutoAugment(AA) Cubuk et al., 2019

Auto-augment: 여러 augmentation 기법 중 최적 기법을 강화학습으로 탐색한 기법.

Operation Name	Description	Range of magnitudes
ShearX(Y)	Shear the image along the horizontal (vertical) axis with rate *magnitude*.	[-0.3,0.3]
TranslateX(Y)	Translate the image in the horizontal (vertical) direction by *magnitude* number of pixels.	[-150,150]
Rotate	Rotate the image *magnitude* degrees.	[-30,30]
AutoContrast	Maximize the the image contrast, by making the darkest pixel black and lightest pixel white.	
Invert	Invert the pixels of the image.	
Equalize	Equalize the image histogram.	
Solarize	Invert all pixels above a threshold value of *magnitude*.	[0,256]
Posterize	Reduce the number of bits for each pixel to *magnitude* bits.	[4,8]
Contrast	Control the contrast of the image. A *magnitude*=0 gives a gray image, whereas *magnitude*=1 gives the original image.	[0.1,1.9]
Color	Adjust the color balance of the image, in a manner similar to the controls on a colour TV set. A *magnitude*=0 gives a black & white image, whereas *magnitude*=1 gives the original image.	[0.1,1.9]
Brightness	Adjust the brightness of the image. A *magnitude*=0 gives a black image, whereas *magnitude*=1 gives the original image.	[0.1,1.9]
Sharpness	Adjust the sharpness of the image. A *magnitude*=0 gives a blurred image, whereas *magnitude*=1 gives the original image.	[0.1,1.9]
Cutout [25, 72]	Set a random square patch of side-length *magnitude* pixels to gray.	[0,60]
Sample Pairing [50, 73]	Linearly add the image with another image (selected at random from the same mini-batch) with weight *magnitude*, without changing the label.	[0, 0.4]

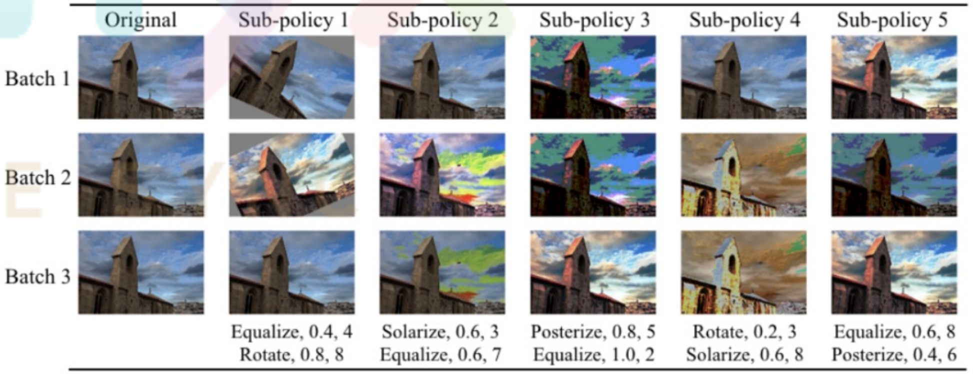


Figure 3. One of the successful policies on ImageNet. As described in the text, most of the policies found on ImageNet used color-based transformations.

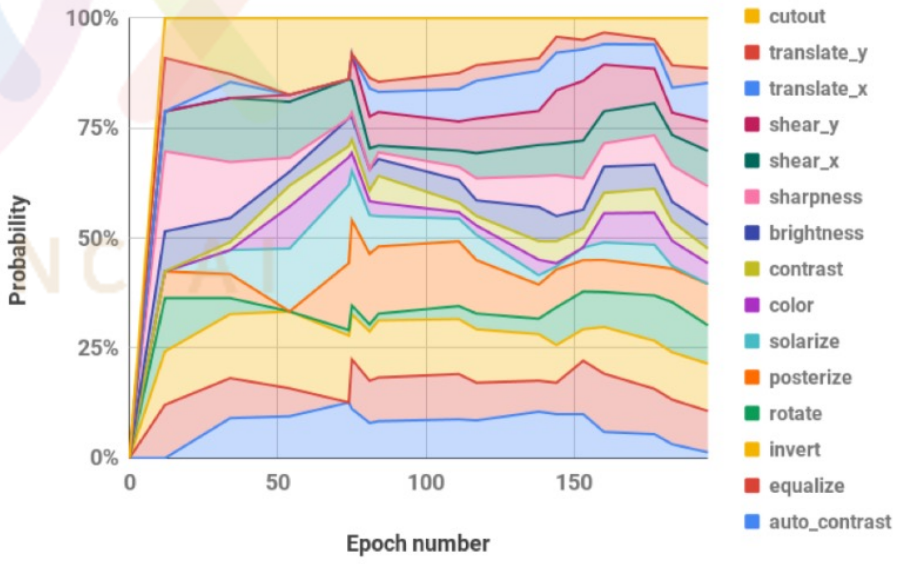
논문 주소 https://arxiv.org/abs/1805.09501

Population-Based Augmentation (PBA)

Population based augmentation과 Fast auto-augmentation: Auto-augmentation에 성능을 유지하면서 학습 시간을 급격하게 줄인 데이터 증강 기법으로, 고도화된 강화학습과 베이지안 최적화를 응용하였음.

Dataset	Value	Previous Best	AA	PBA
CIFAR-10	GPU Hours	-	5000	5
	Test Error	2.1	1.48	1.46
CIFAR-100	GPU Hours	-	0*	0*
	Test Error	12.2	10.7	10.9
SVHN	GPU Hours	-	1000	1
	Test Error	1.3	1.0	1.1

Table 1. Comparison of pre-computation costs and test set error (%) between this paper, AutoAugment (AA), and the previous best published results.

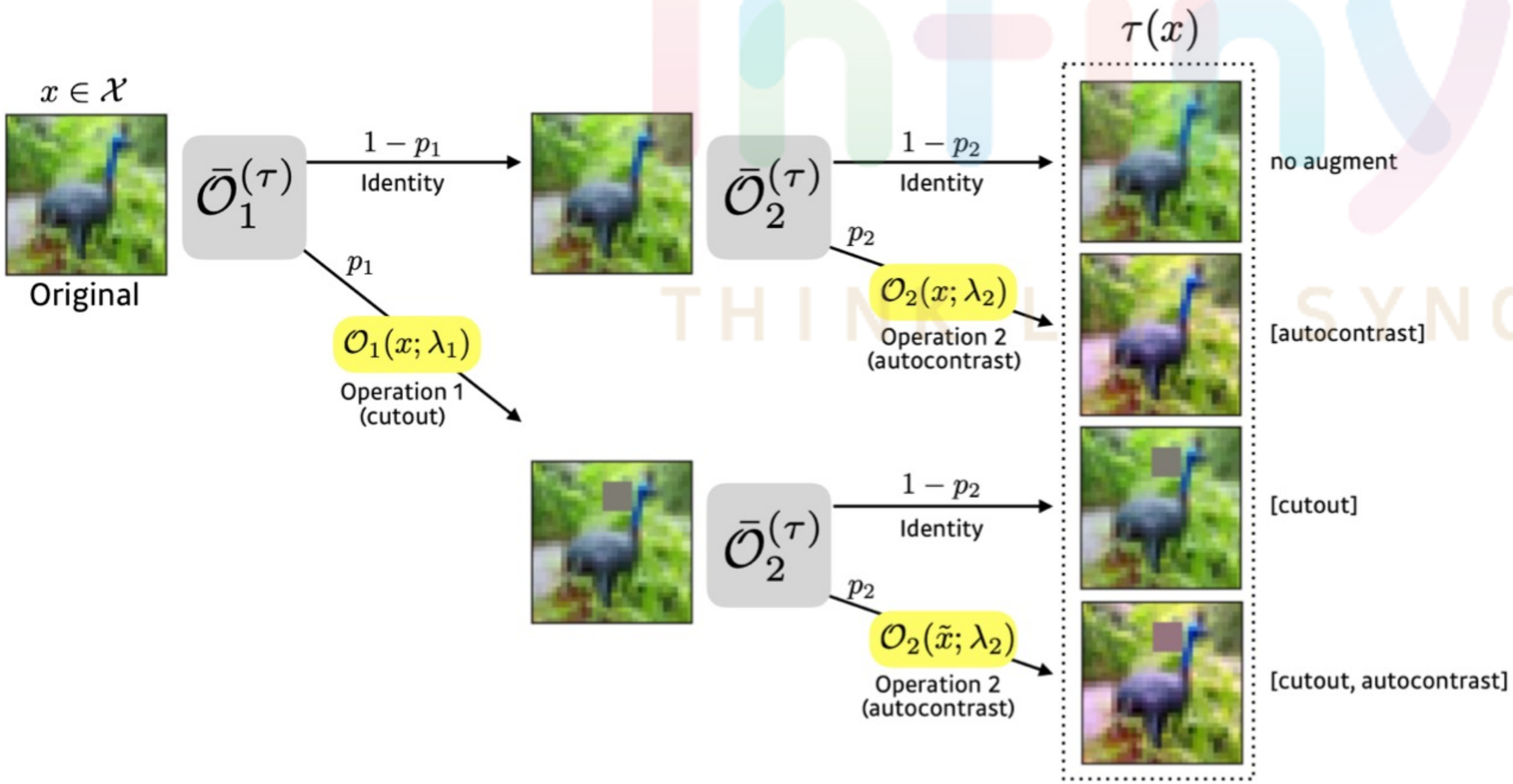


(b) Normalized plot of operation probability parameters over time. The distribution flattens out towards the end of training.

논문 주소 : https://arxiv.org/abs/1905.05393v1

Fast AutoAugment(Fast AA)

AutoAugmentation의 계산 속도를 개선하기 위한 -> 버전



Dataset	AutoAugment [3]	Fast AutoAugment
CIFAR-10	5000	3.5
SVHN	1000	1.5
ImageNet	15000	450

Table 1: GPU hours comparison of Fast AutoAugment with AutoAugment.

Model	Baseline	AutoAugment [3]	Fast AutoAugment
ResNet-50	23.7 / 6.9	**22.4 / 6.2**	**22.4** / 6.3
ResNet-200	21.5 / 5.8	20.00 / 5.0	**19.4 / 4.7**

Table 5: Validation set Top-1 / Top-5 error rate (%) on ImageNet.

논문주소 : https://arxiv.org/abs/1905.00397

RandAugment (RA) Cubuk et al., 2020

- Rand-augment: 랜덤성을 기반하여, 매 iteration마다 다른 augmentation 기법을 적용하는 데이터 증강 기법.

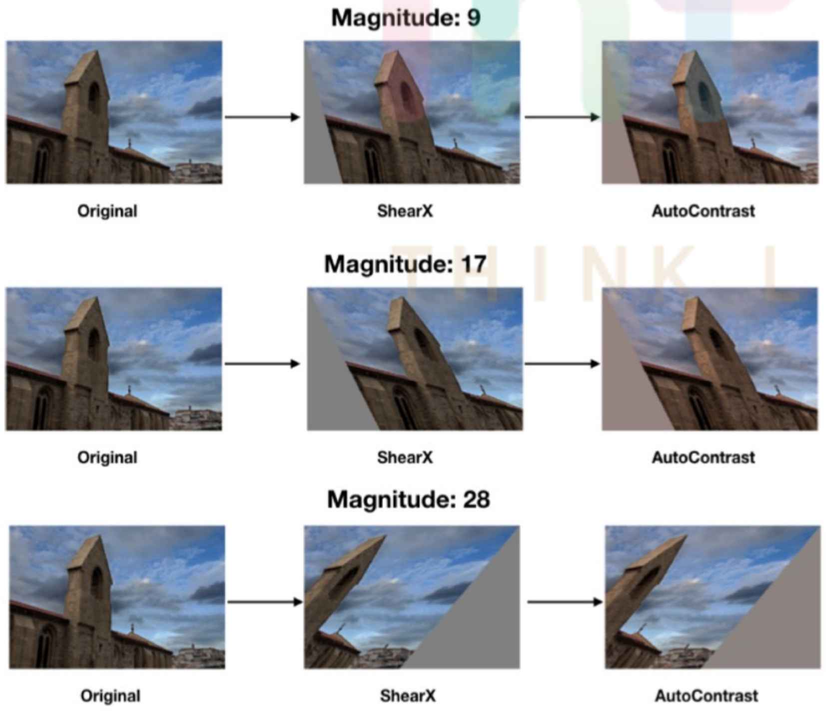


Figure 1. **Example images augmented by RandAugment.**

	baseline	PBA	Fast AA	AA	RA
CIFAR-10					
Wide-ResNet-28-2	94.9	-	-	**95.9**	95.8
Wide-ResNet-28-10	96.1	**97.4**	97.3	**97.4**	97.3
Shake-Shake	97.1	**98.0**	**98.0**	**98.0**	**98.0**
PyramidNet	97.3	**98.5**	98.3	**98.5**	**98.5**
CIFAR-100					
Wide-ResNet-28-2	75.4	-	-	**78.5**	78.3
Wide-ResNet-28-10	81.2	**83.3**	82.7	82.9	**83.3**
SVHN (core set)					
Wide-ResNet-28-2	96.7	-	-	98.0	**98.3**
Wide-ResNet-28-10	96.9	-	-	98.1	**98.3**
SVHN					
Wide-ResNet-28-2	98.2	-	-	**98.7**	**98.7**
Wide-ResNet-28-10	98.5	98.9	98.8	98.9	**99.0**

Table 2. **Test accuracy (%) on CIFAR-10, CIFAR-100, SVHN and SVHN core set.**

논문 주소 : https://arxiv.org/abs/1909.13719

과제 자료 정리 및 학습

목　　적　: 인공지능 경우 최신논문을 보고 정리하는 습관이 필요

과 제 명　: 설명해준 논문 중 1개를 선택하여 읽어 보고 정리하여 제출

제출 제한 사항 : 최소 한논문당 2장 이상 정리

제출　일자 : 5월 27일 오전 9시 까지

감사합니다.

THINK LIFE SYNC AI

Infinyx