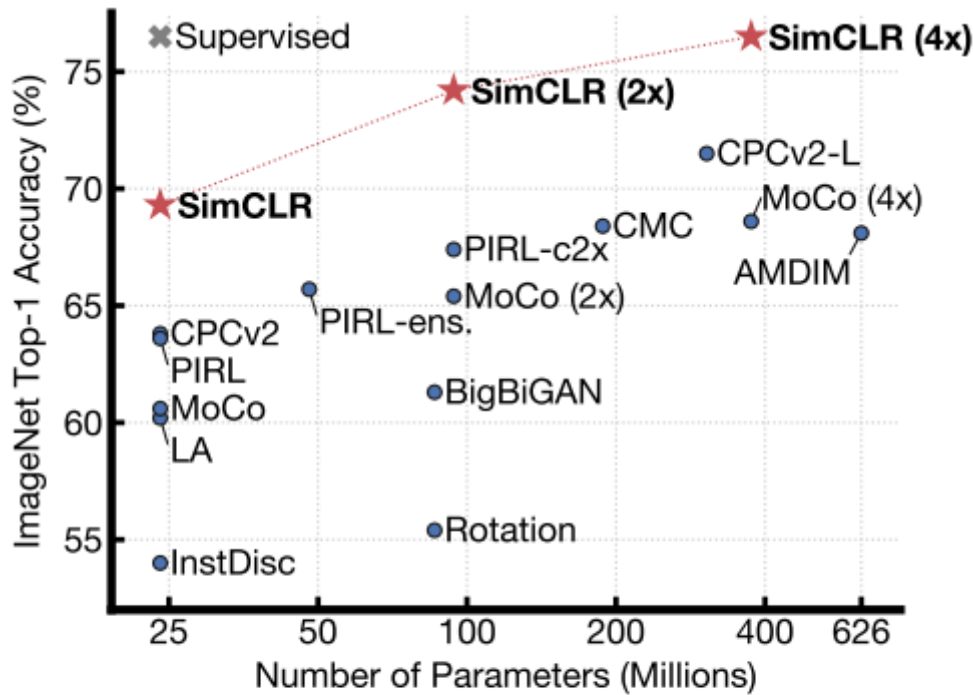


## 7.5. A Simple Framework for Contrastive Learning of Visual Representations

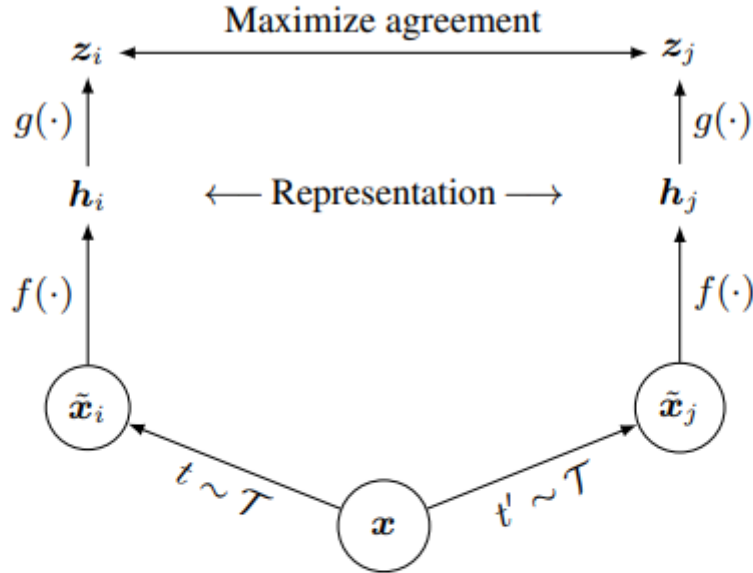
요약

- Data augmentation이 중요한 역할을 한다.
- Representation과 Contrastive loss사이에 Nonlinear Transformation를 도입한다.
- Supervised보다 훨씬 큰 batch size와 더욱 많은 epochs동안 학습시킨다.

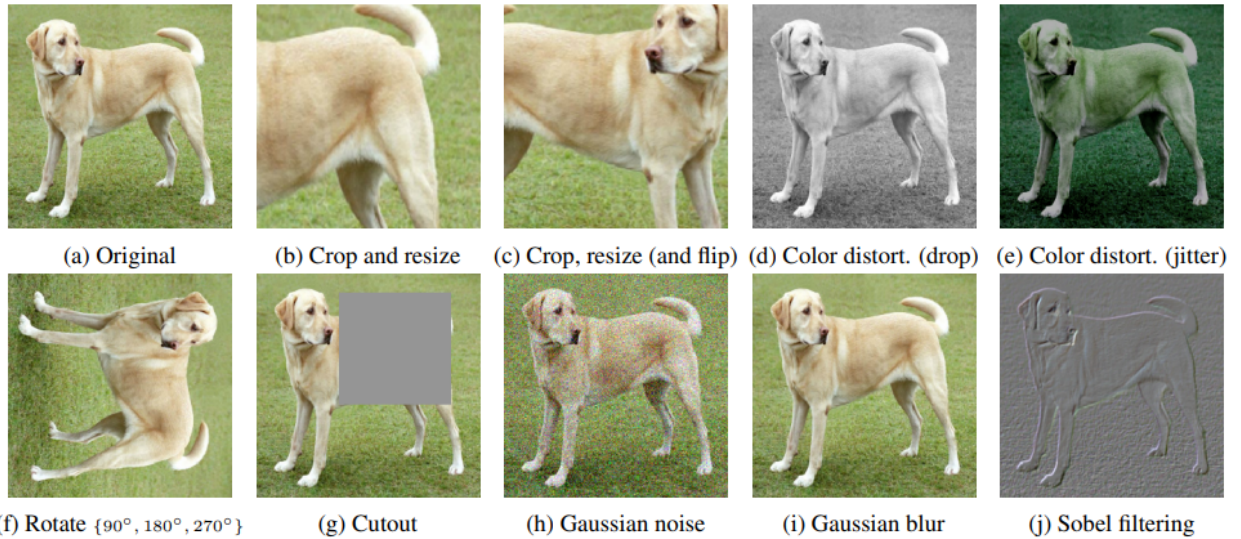
- 
- Contrastive prediction task를 정의할때 Data augmentation의 구성이 중요하고, Unsupervised contrastive learning은 Supervised보다 많은 Data augmentation을 이용해야 한다.
  - Representation과 Contrastive Loss 사이에 Nonlinear transformation을 도입하면 성능이 좋아진다.
  - Normalized embedding과 Temperature parameter를 사용한 Contrastive cross entropy loss를 이용한다.
  - Supervised와 비교해서 더 큰 batch size와 더 긴 training epoch을 사용해야 한다.
  - Supervised처럼 네트워크가 깊고 넓을수록 성능이 좋다.



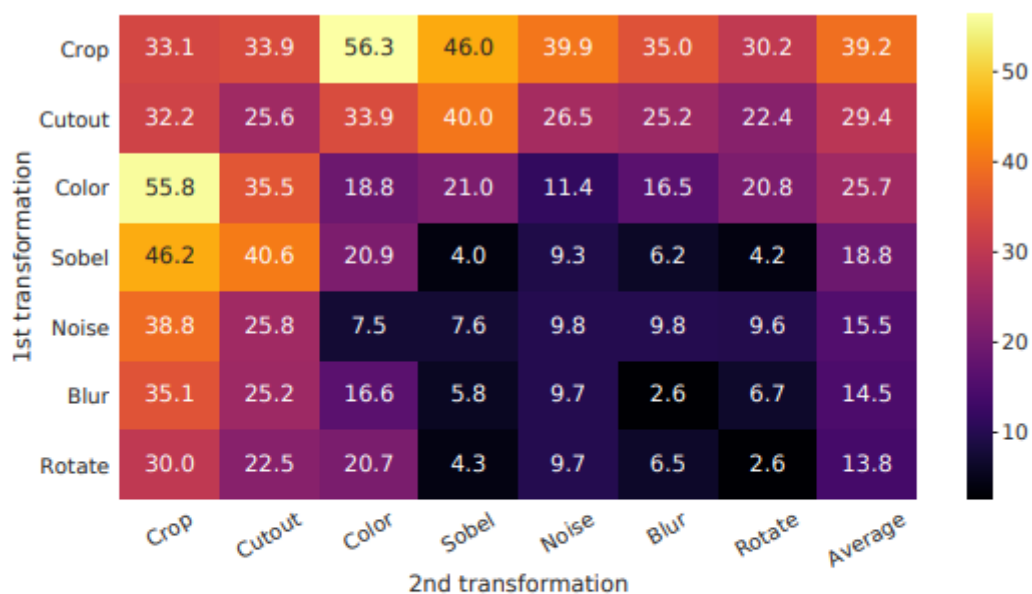
*Figure 1.* ImageNet Top-1 accuracy of linear classifiers trained on representations learned with different self-supervised methods (pretrained on ImageNet). Gray cross indicates supervised ResNet-50. Our method, SimCLR, is shown in bold.



**Figure 2.** A simple framework for contrastive learning of visual representations. Two separate data augmentation operators are sampled from the same family of augmentations ( $t \sim \mathcal{T}$  and  $t' \sim \mathcal{T}$ ) and applied to each data example to obtain two correlated views. A base encoder network  $f(\cdot)$  and a projection head  $g(\cdot)$  are trained to maximize agreement using a contrastive loss. After training is completed, we throw away the projection head  $g(\cdot)$  and use encoder  $f(\cdot)$  and representation  $\mathbf{h}$  for downstream tasks.



**Figure 4.** Illustrations of the studied data augmentation operators. Each augmentation can transform data stochastically with some internal parameters (e.g. rotation degree, noise level). Note that we *only* test these operators in ablation, the *augmentation policy* used to train our models only includes *random crop (with flip and resize)*, *color distortion*, and *Gaussian blur*. (Original image cc-by: Von.grzanka)



*Figure 5.* Linear evaluation (ImageNet top-1 accuracy) under individual or composition of data augmentations, applied only to one branch. For all columns but the last, diagonal entries correspond to single transformation, and off-diagonals correspond to composition of two transformations (applied sequentially). The last column reflects the average over the row.