A Simple Framework for Contrastive Learning of Visual Representations

SimCLR review

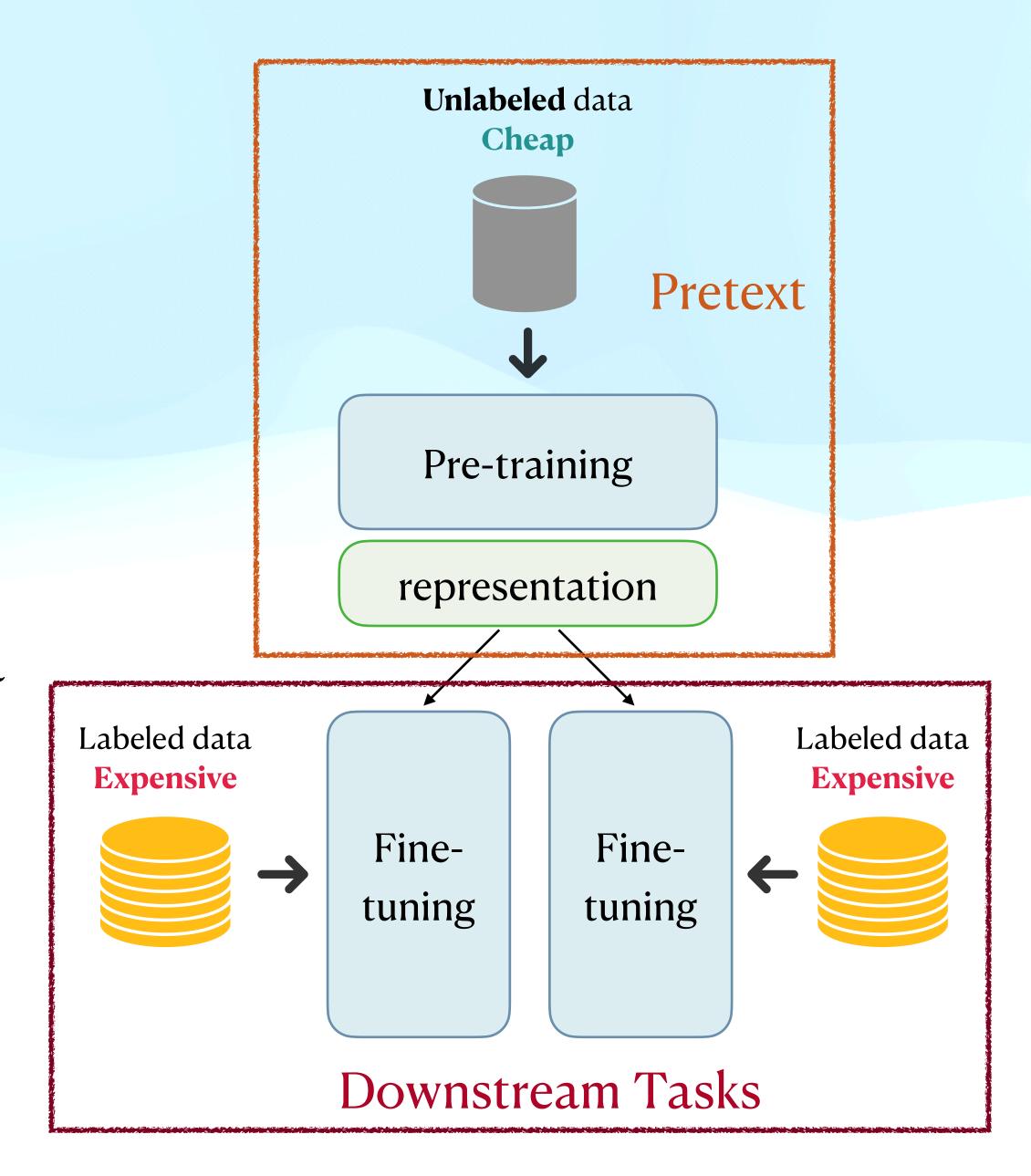
Background

Self-supervised Learning

• "Unsupervised pre-training, Supervised fine-tuning"

• Pretext is task-agnostic, we train the model (Encoder) with a large amount of unlabeled data

• Downstream task is task-specific, we train the model with a **few** amount of labeled data (1% to 10%)

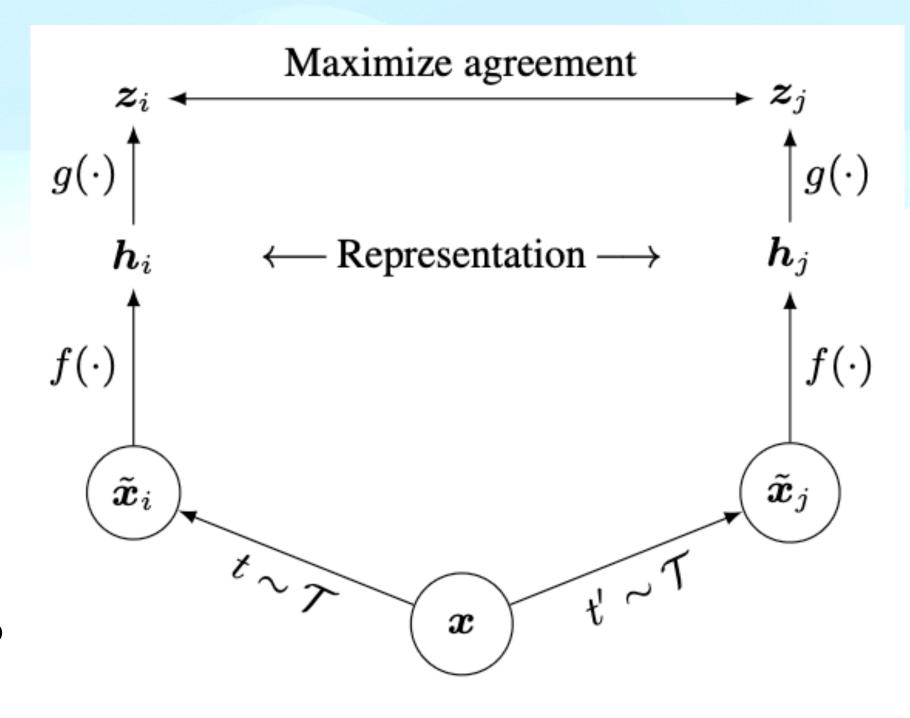


Framework

Paper abstract

Findings/Contributions

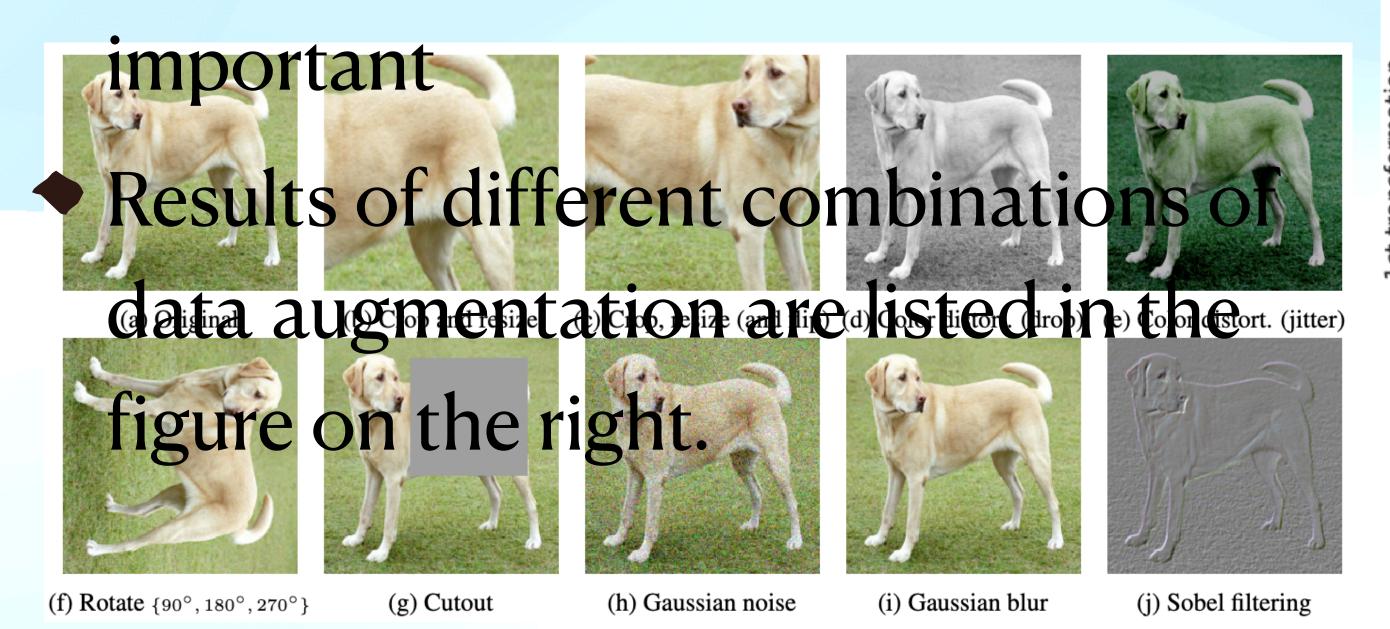
- Composition of data augmentations is important
- Functionality of projection head (nonlinear transformation)
- Larger batch size and longer training steps benefits SSL more than supervised model.

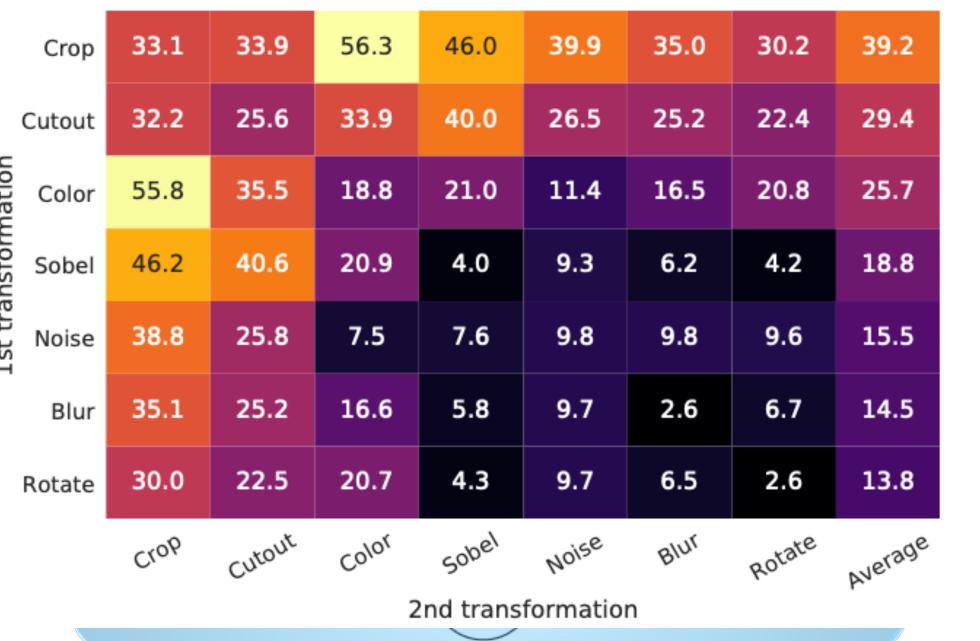


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Data Augmentations Finding 1

Composition of data augmentations is



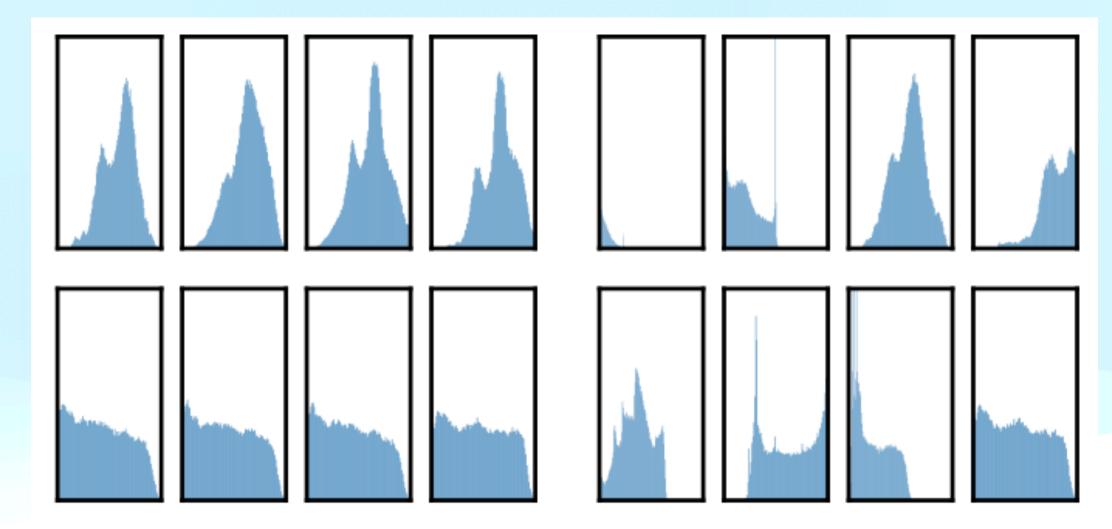


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Data Augmentations Finding 1

 Color distortion suffice to distinguish the image with similar color distributions after random cropping.



(a) Without color distortion.

(b) With color distortion.

Color distortion

SSL need stronger data augmentations

	Color distortion strength					
Methods	1/8	1/4	1/2	1	1 (+Blur)	AutoAug
SimCLR Supervised	59.6 77.0	61.0 76.7	62.6 76.5	63.2 75.7	64.5 75.4	61.1 77.1

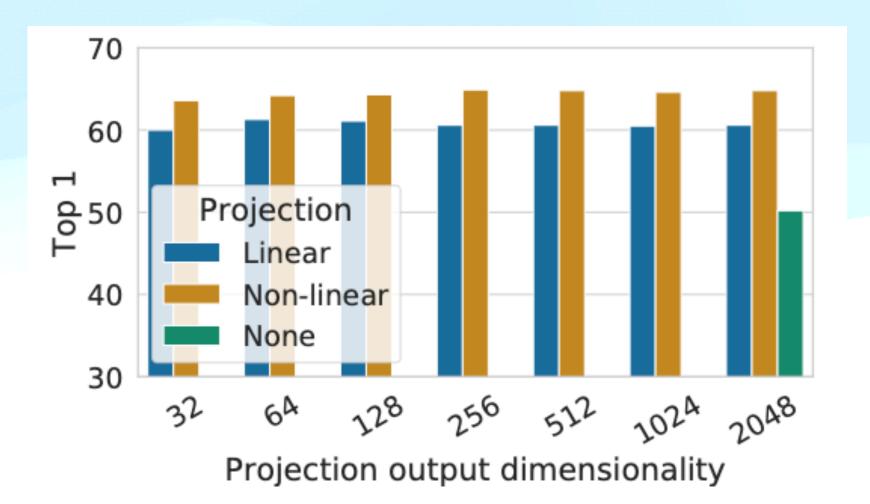
Different level of color distortion

Projection Head Finding 2

A nonlinear projection head improves the representation quality of the layer before it.

◆ Default setting is MLP and nonlinear ReLU.

More information is contained before projection than after, e.g, the augmentation operation.



 What to predict?
 Random guess
 Representation h g(h)

 Color vs grayscale
 80
 99.3
 97.4

 Rotation
 25
 67.6
 25.6

 Orig. vs corrupted
 50
 99.5
 59.6

 Orig. vs Sobel filtered
 50
 96.6
 56.3

Intensive TrainingFinding 3

◆ Contrastive learning benefits more from larger batch size and longer training.

