

A Simple Framework for Contrastive Learning of Visual Representations

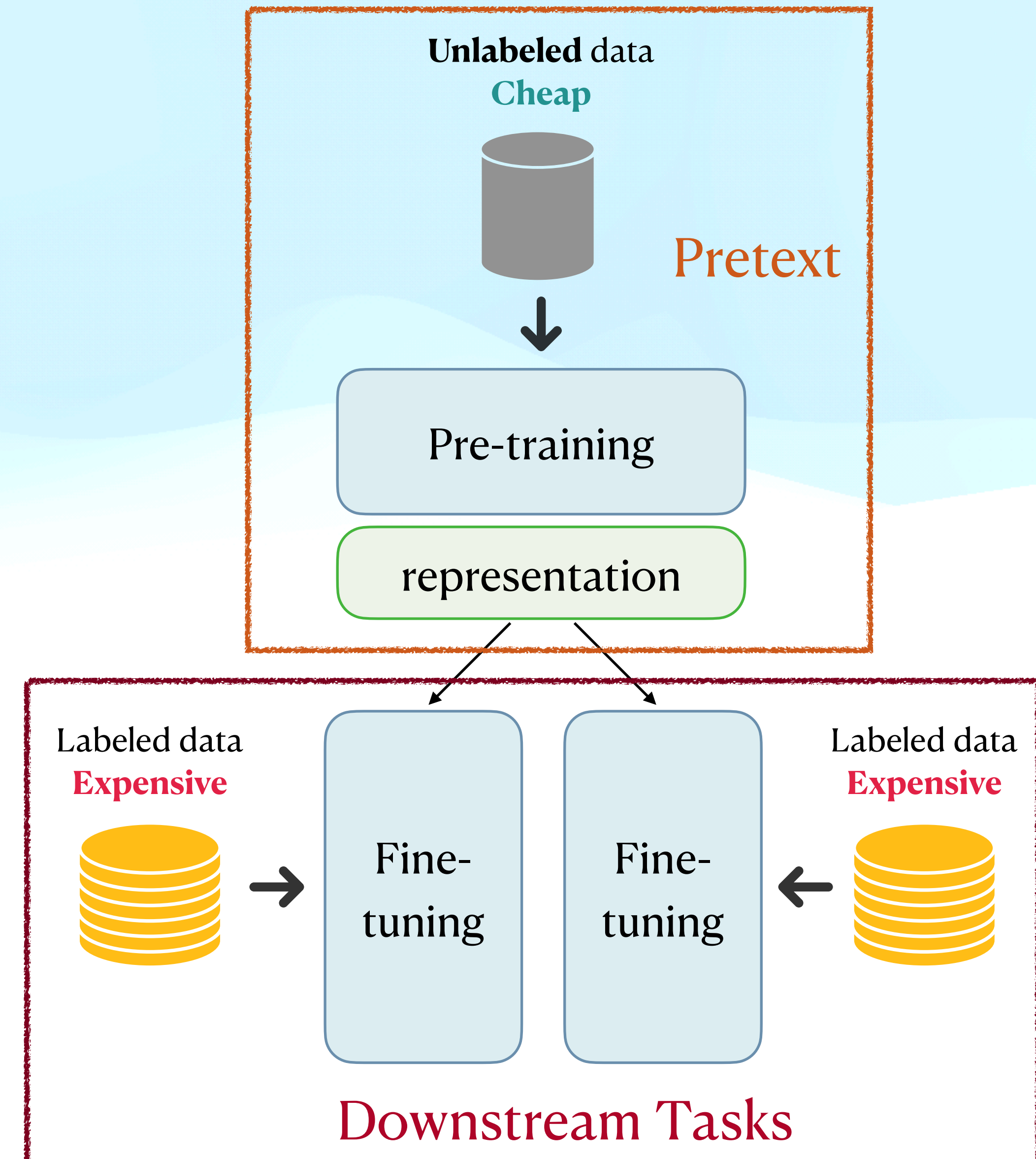
SimCLR review

YU MO, 2022/06/27

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%)

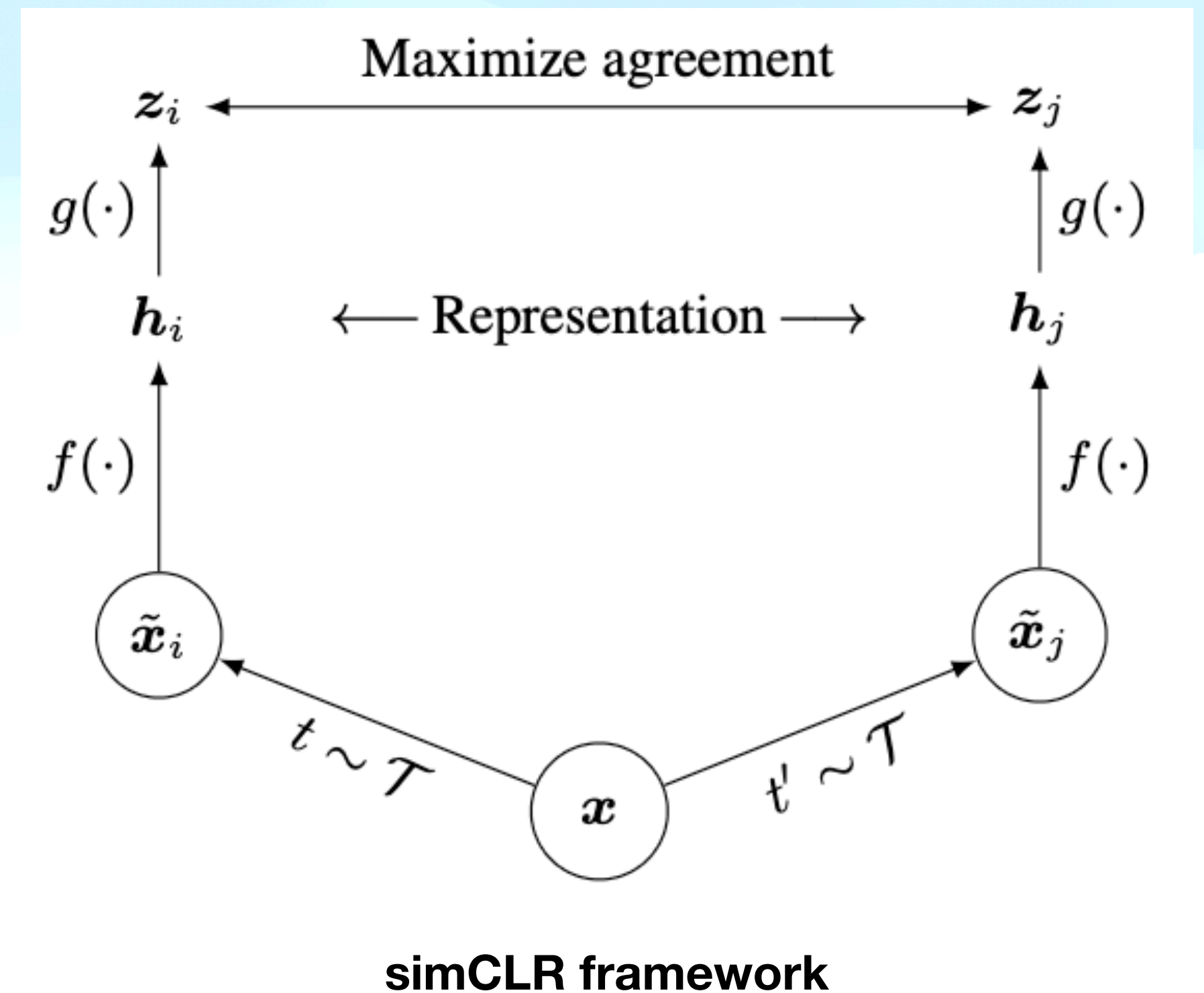


Framework

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.

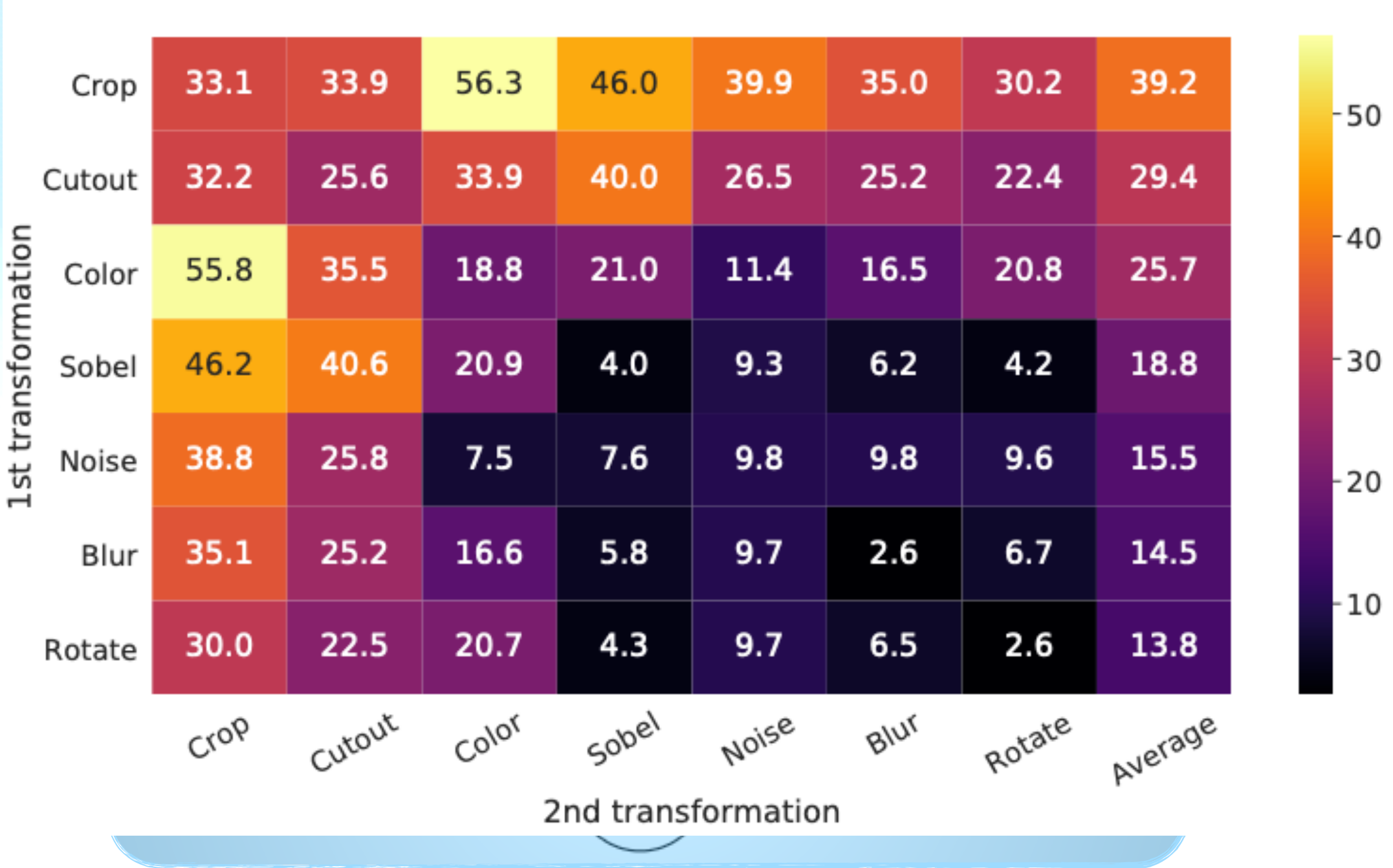
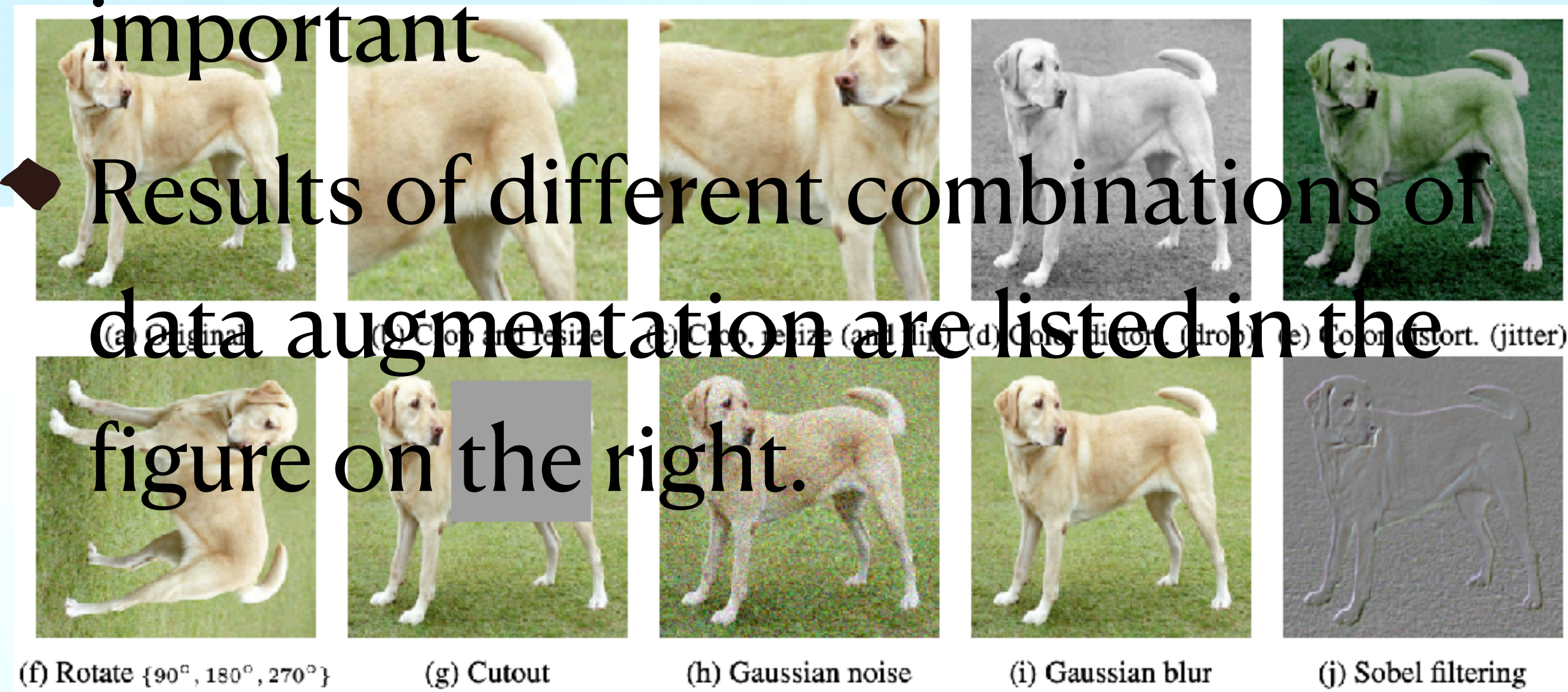


Data Augmentations

Finding 1

◆ Composition of data augmentations is important

◆ Results of different combinations of data augmentation are listed in the figure on the right.



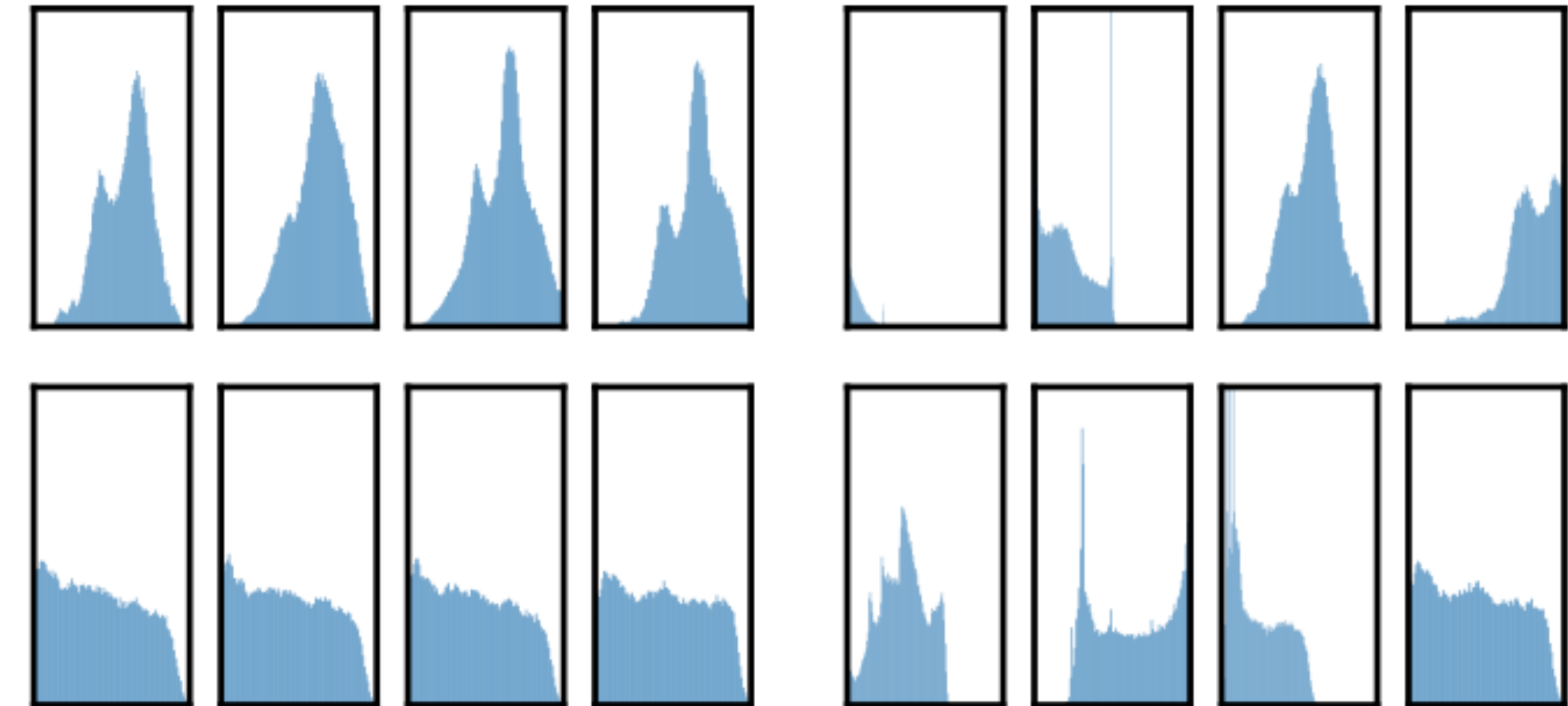
simCLR framework

Data Augmentations

Finding 1

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

◆ SSL need stronger data augmentations



(a) Without color distortion. (b) With color distortion.

Color distortion

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

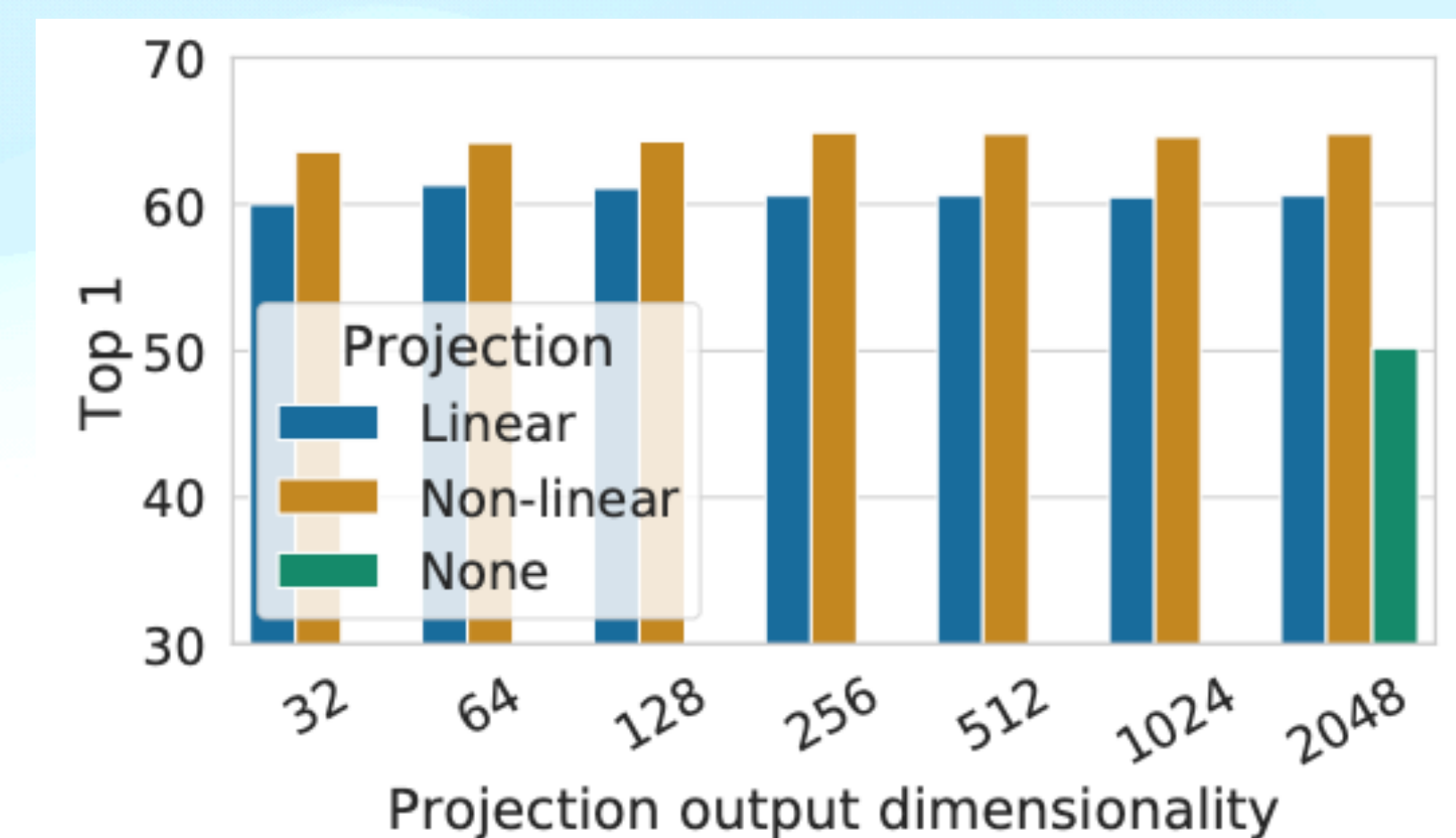
Different level of color distortion

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 Training

Finding 3

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

