Evaluation of Self-Supervised Learning Frameworks – SimCLR and RotNet

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Introduction

Self-supervised learning (SSL) enables models to learn the representation of unlabeled data, In this work, we examine SimCLR and RotNet. They utilize different image transformation and objectives to learn the representation of image. Below is the basic framework of the two SSL method.

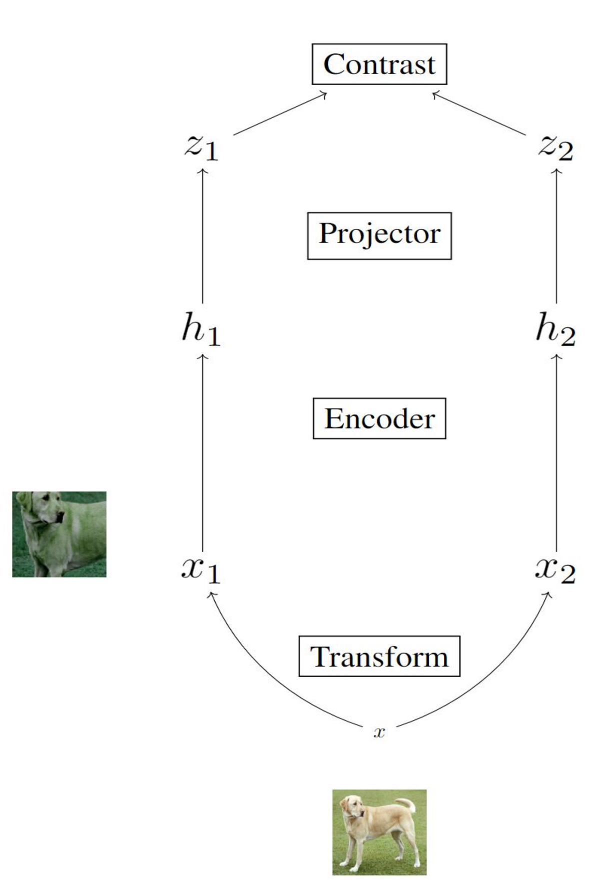

Figure 1: SimCLR

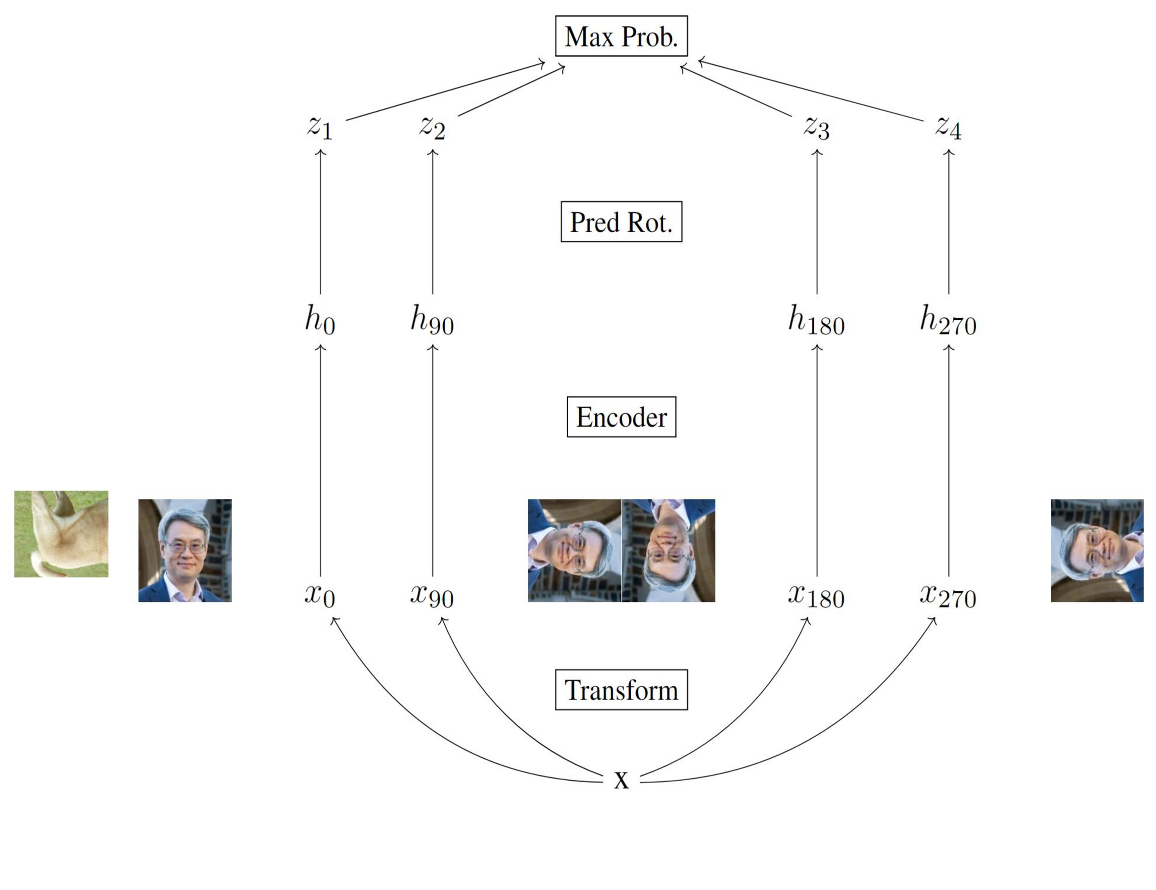

Figure 2: RotNet

Methodology

Framework	SimCLR	RotNet
Transformation	Crop, Color Jitter, Resize, ...	Rotate (0°, 90°, 180°, 270°)
Encoder	ResNet-50	
Projector	MLP	Linear
Objective	Minimize Contrastive Loss	Minimize Classification Loss

Linear Evaluation: We follow the conventional protocol by appending a linear classifier below the frozen pretrained encoder and train on labeled data.

Semi-Supervised Learning: We take the pretrained encoder, append a linear classifier, and fine-tuned on fraction of training data.

Adversarial Attack: We take the fine-tuned model from semi-supervised learning, and perform whitebox PGD/FGSM attack.

Transfer Learning: Using SimCLR framework, we pretrain the model on one dataset, and perform linear evaluation using a different dataset.

Self-Supervised Linear Evaluation

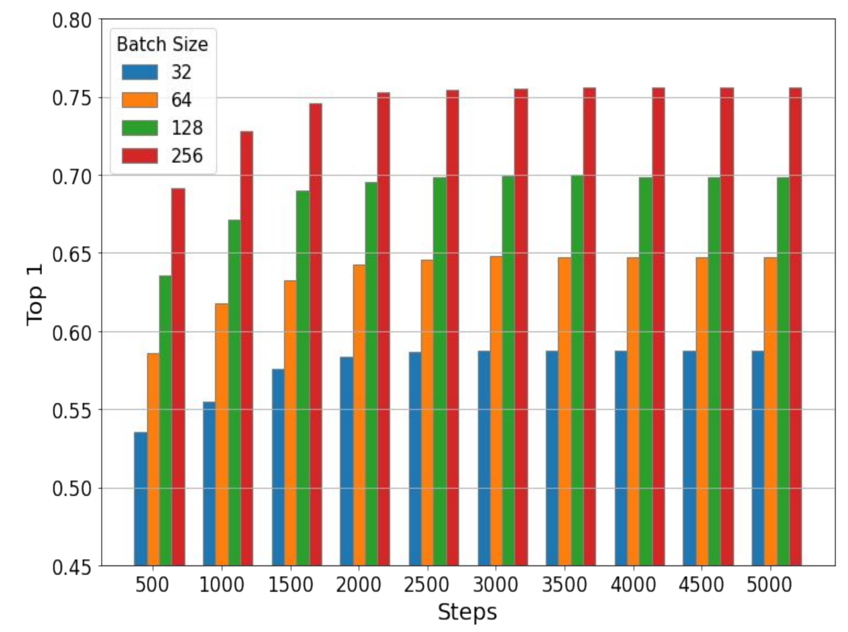

Figure 3: SimCLR

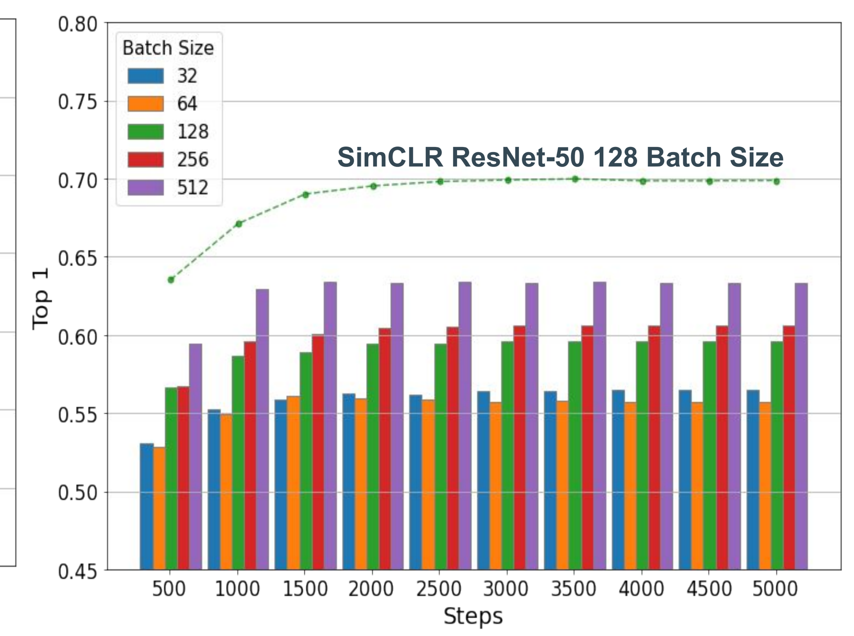

Figure 4: RotNet

- Both SimCLR and RotNet benefits from larger batch size and steps.
- SimCLR outperforms RotNet under the same conditions.

Comparison of Semi-Supervised Learning

Metric	Supervised ResNet-50			Fine-tuned RotNet			Fine-tuned SimCLR		
	1%	10%	50%	1%	10%	50%	1%	10%	50%
Top-1 Accuracy	0.141	0.373	0.475	0.515	0.560	0.577	0.653	0.822	**0.870**
Top-2 Accuracy	0.260	0.539	0.682	0.721	0.760	0.771	0.822	0.929	**0.953**
AUC	0.634	0.787	0.873	0.881	0.899	0.909	0.935	0.981	**0.990**

- SSL pretrained models outperform supervised model after fine-tuning.
- SimCLR pretrained weights are more effective than RotNet.
- RotNet does not learn a good representation for semi-supervised task.

Whitebox Adversarial Attack (SimCLR)

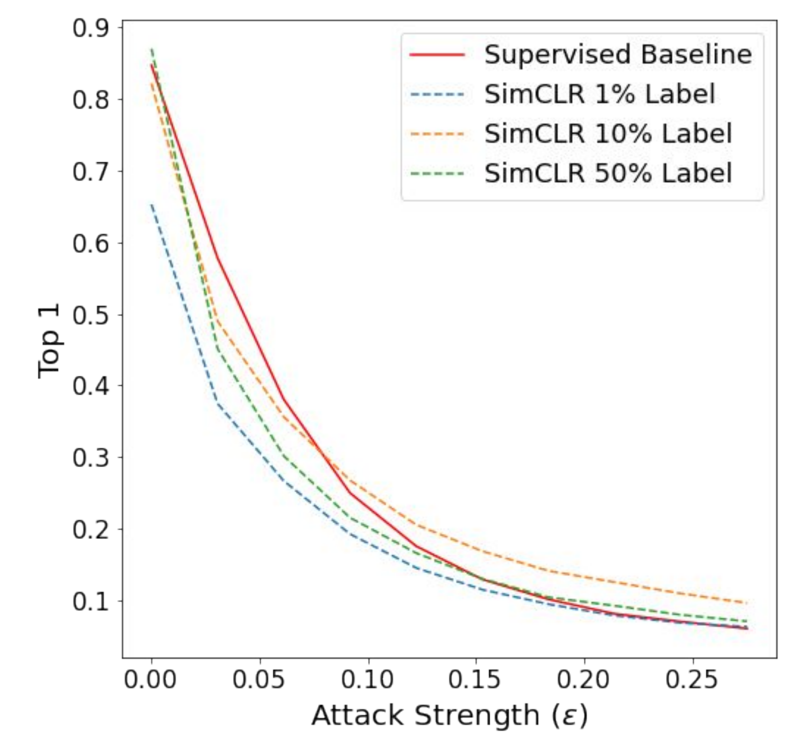

Figure 5: PGD

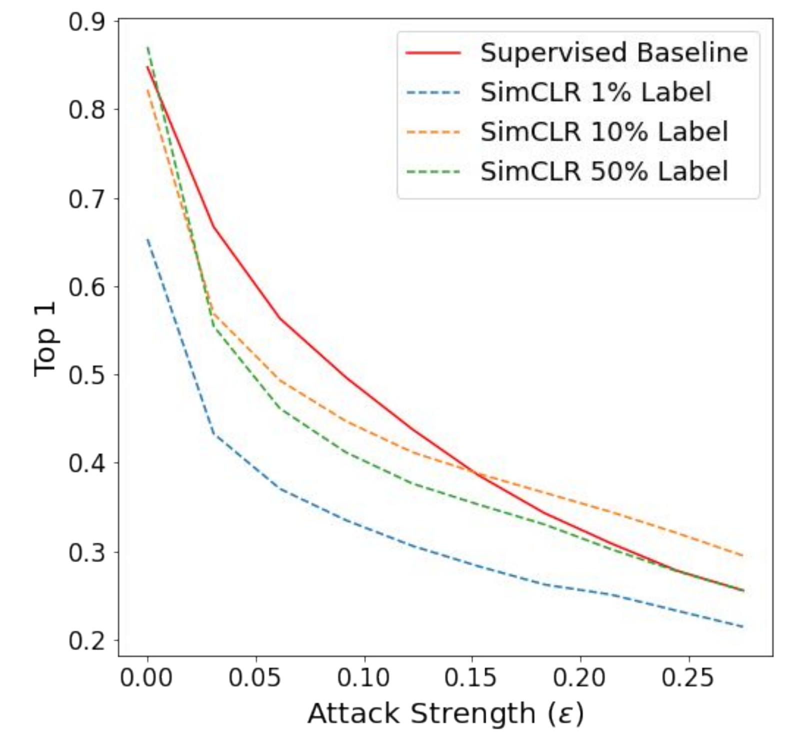

Figure 6: FGSM

- SimCLR pretrained and finetuned model is more sensitive to adversarial attacks than supervised learning method.
- Both methods are not robust toward adversarial attacks.

Transfer Learning (SimCLR)

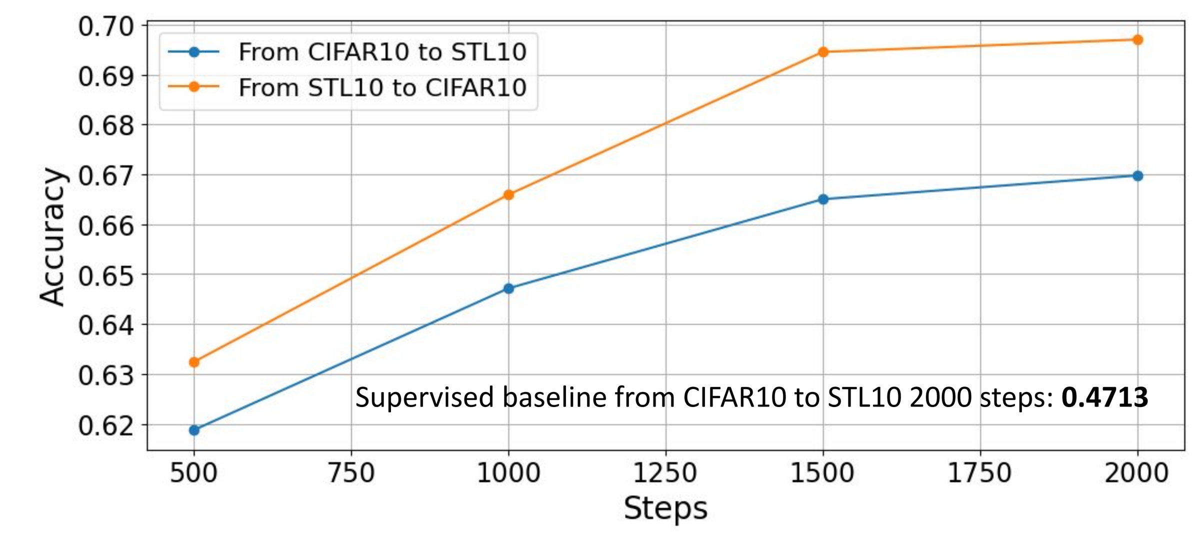

Figure 7: SimCLR Transfer Learning

Batch Size = 128

SimCLR CIFAR to STL (5000 steps)

Batch	Top-1
32	0.5716
64	0.6304
128	0.6740
256	**0.7105**

- SimCLR pretrained model shows high transferability for both dataset.
- Larger pretrained dataset (STL10) increase transfer learning accuracy.
- Transfer learning accuracy also benefits from larger batch size.

Conclusion

We found that both self-supervised learning methods can learn representation of images, the learned representations are good backbones for classification tasks. In addition, they can outperform supervised methods in semi-supervised and transfer learning settings under limited iterations.

In contrast, we also noticed that self-supervised models using self-supervised representations are more sensitive to certain adversarial attacks.

Using the same encoder (ResNet-50), SimCLR outperforms RotNet likely because it uses more diverse image transformations to extract features and a designated contrastive learning objective. On the other hand, RotNet, is much more computationally efficient. It is worth noting that the original RotNet paper achieves high performance using AlexNet as an encoder, which has 3x more parameters.

We also tested both SSL method with a smaller encoder (ResNet-18) and observed that both SSL methods require a relatively complex architecture to learn meaningful representation.

References

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2. Gidaris et al., "Unsupervised Representation Learning by Predicting Image Rotations", 2018
3. Rohit Gupta, Naveed Akhtar, Ajmal Mian, Mubarak Shah: "Contrastive Self-Supervised Learning Leads to Higher Adversarial Susceptibility", 2022
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