Improving Transferability of Representations via Augmentation-Aware Self-Supervision

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TL; DR. Learning augmentation-aware information by predicting the difference between two augmented samples improves the transferability of representations for various downstream tasks.

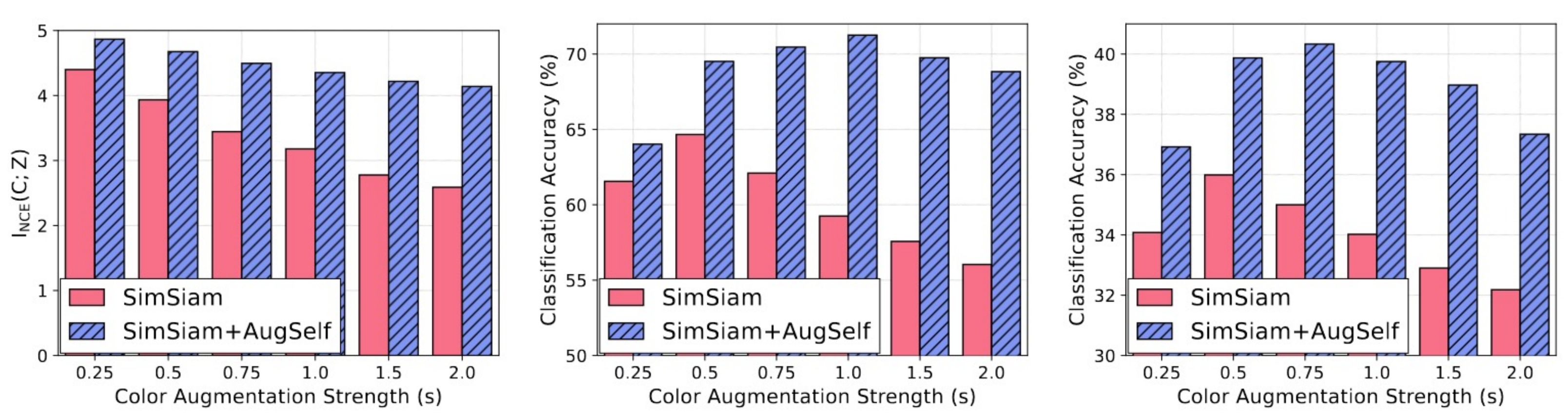
Background & Motivation

Self-supervised learning (SSL) learns representations via a pretext task that requires to predict self-supervision constructed from only input signals. Recent SSL methods often aim at learning invariance to data augmentations

- Contrastive methods (e.g., MoCo [1], SimCLR [2])
- Negative-free methods (e.g., BYOL [3], SimSiam [4])
- Clustering-based methods (e.g., SwAV [5])

Question: is learning invariance to a given set of augmentations always beneficial to representation learning? To answer this question,

- Pretrain ResNet-18 on STL10 with varying color jittering strength s.
- Compute mutual information between the learned representation Z=f(x) and color information C(x) encoded by color histograms.
- Transfer the learned representation to color-sensitive downstream tasks.



(a) Mutual information (b) STL10→Flowers (c) STL10→Food

Observations:

- Stronger color augmentations ⇒ color-relevant information loss
- Less color information ⇒ performance drop in color-sensitive tasks

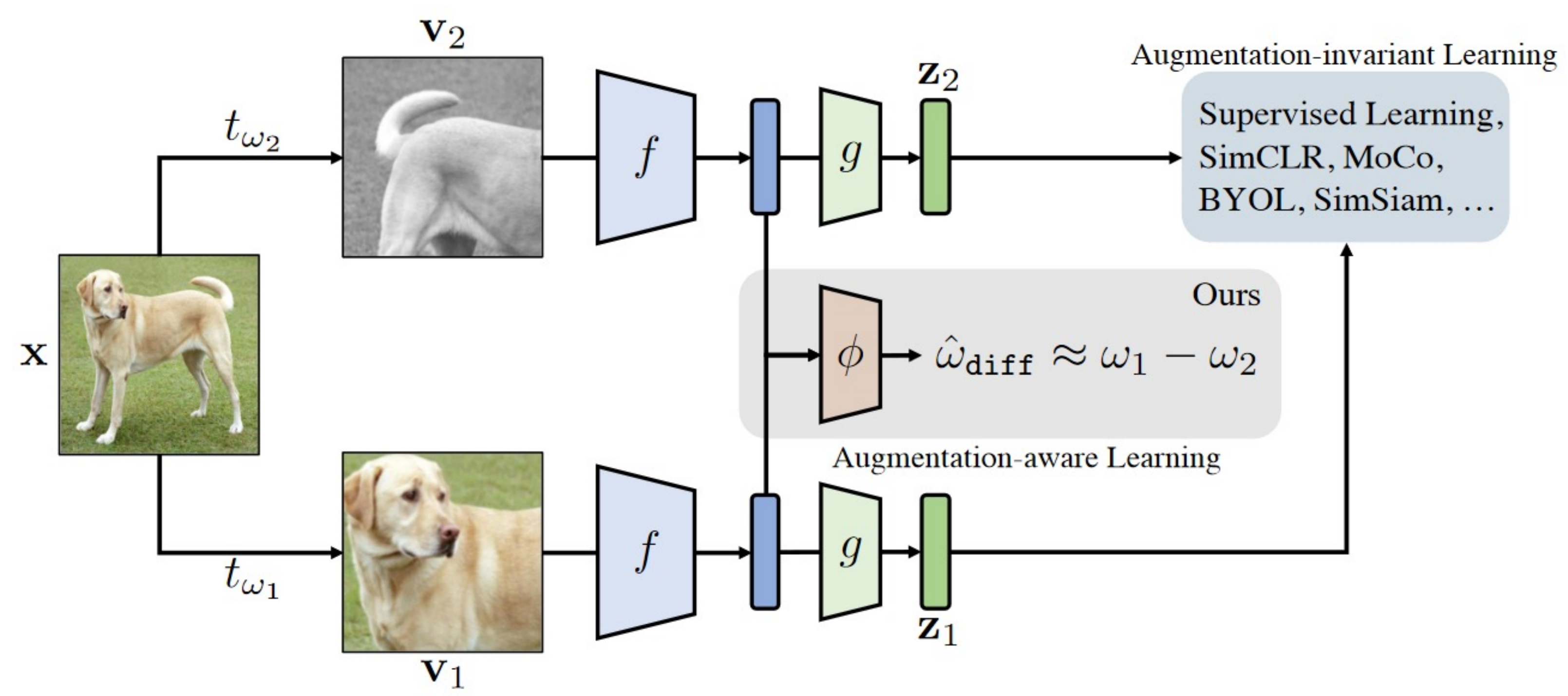
Research Question: how to prevent the information loss comes from learning the invariance?

Summary of Contribution

- For learning augmentation-aware information, we suggest to optimize an auxiliary self-supervised loss (**AugSelf**) that learns to predict difference between augmentation parameters of two randomly augmented samples.
- Extensive experiments demonstrate that (1) **AugSelf** can improve learned representations' transferability for various downstream tasks, and also (2) **AugSelf** can be easily incorporated with recent SSL methods with a negligible additional training cost.

Method

Notation. $\mathbf{x}$ is an original input image. t_ω is an augmentation function parameterized by ω. $\mathbf{v} = t_\omega(\mathbf{x})$ is the augmented sample of $\mathbf{x}$ by t_ω. f is a CNN feature extractor such as ResNet. g is a projection MLP that is widely used in recent SSL methods [1-5]. ϕ is a prediction MLP for AugSelf.



For learning augmentation-aware information, we learn to predict the difference between two augmented samples. Formally, auxiliary augmentation-aware self-supervised loss (**AugSelf**) is defined by

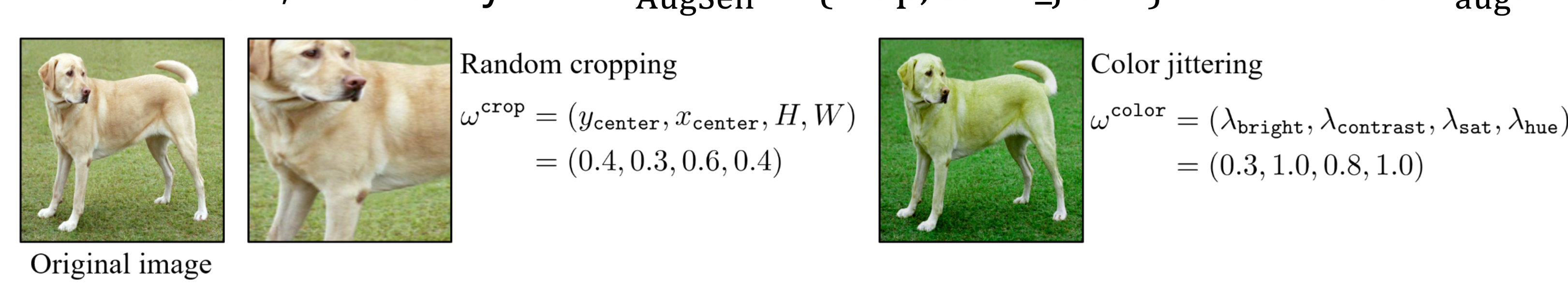
$$\mathcal{L}_{\texttt{AugSelf}}(\mathbf{x}, \omega_1, \omega_2; \theta) = \sum_{\text{aug} \in \mathcal{A}_{\texttt{AugSelf}}} \mathcal{L}_{\text{aug}}\left(\phi_\theta^{\text{aug}}(f_\theta(\mathbf{v}_1), f_\theta(\mathbf{v}_2)), \omega_{\texttt{diff}}^{\text{aug}}\right)$$

where $\omega_{\text{diff}}^{\text{aug}}$ is the difference between augmentation-specific parameters.

Benefits of AugSelf: it can …

- preserve augmentation-aware information for downstream tasks
- be easily incorporated with [1-5] thanks to its self-supervision design

In this work, we mainly use $\mathcal{A}_{\text{AugSelf}} = \{\text{crop}, \text{color\_jitter}\}$ and MSE for $\mathcal{L}_{\text{aug}}$.



References

[1] He et al., Momentum Contrast for Unsupervised Visual Representation Learning, CVPR 2020
[2] Chen et al., A Simple Framework for Contrastive Learning of Visual Representations, ICML 2020
[3] Grill et al., Bootstrap your own latent: A new approach to self-supervised Learning, 2020
[4] Chen & He, Exploring Simple Siamese Representation Learning, 2020
[5] Caron et al., Unsupervised Learning of Visual Features by Contrasting Cluster Assignments, NIPS 2020

Experiment

SelfAug improves the transferability of representations in various standard (first table) and few-shot (second table) downstream classification tasks

Method	CIFAR10	CIFAR100	Food	MIT67	Pets	Flowers	Caltech101	Cars	Aircraft	DTD	SUN397
ImageNet100-pretrained ResNet-50											
SimSiam	86.89	66.33	61.48	65.75	74.69	88.06	84.13	**48.20**	48.63	65.11	50.60
+ AugSelf	**88.80**	**70.27**	**65.63**	**67.76**	**76.34**	**90.70**	**85.30**	47.52	**49.76**	**67.29**	**52.28**
MoCo v2	84.60	61.60	59.37	61.64	70.08	82.43	77.25	33.86	**41.21**	64.47	46.50
+ AugSelf	**85.26**	**63.90**	**60.78**	**63.36**	**73.46**	**85.70**	**78.93**	**37.35**	39.47	**66.22**	**48.52**
Supervised	**86.16**	62.70	53.89	52.91	73.50	76.09	**77.53**	30.61	36.78	61.91	40.59
+ AugSelf	86.06	**63.77**	**55.84**	**54.63**	**74.81**	**78.22**	77.47	**31.26**	**38.02**	**62.07**	**41.49**

	FC100		CUB200		Plant Disease	
Method	(5, 1)	(5, 5)	(5, 1)	(5, 5)	(5, 1)	(5, 5)
ImageNet100-pretrained ResNet-50						
SimSiam	36.19±0.36	50.36±0.38	45.56±0.47	62.48±0.48	75.72±0.46	89.94±0.31
+ AugSelf (ours)	**39.37**±0.40	**55.27**±0.38	**48.08**±0.47	**66.27**±0.46	**77.93**±0.46	**91.52**±0.29
MoCo v2	31.67±0.33	43.88±0.38	41.67±0.47	56.92±0.47	65.73±0.49	84.98±0.36
+ AugSelf (ours)	**35.02**±0.36	**48.77**±0.39	**44.17**±0.48	**57.35**±0.48	**71.80**±0.47	**87.81**±0.33
Supervised	33.15±0.33	46.59±0.37	46.57±0.48	63.69±0.46	68.95±0.47	88.77±0.30
+ AugSelf (ours)	**34.70**±0.35	**48.89**±0.38	**47.58**±0.48	**65.31**±0.45	**70.82**±0.46	**89.77**±0.29

SelfAug can be incorporated with various SSL methods (STL10 pretraining)

Method	AugSelf (ours)	STL10	CIFAR10	CIFAR100	Food	MIT67	Pets	Flowers
SimCLR [2]		84.87	78.93	48.94	31.97	36.82	43.18	56.20
	✓	**84.99**	**80.92**	**53.64**	**36.21**	**40.62**	**46.51**	**64.31**
BYOL [12]		86.73	82.66	55.94	37.30	42.78	50.21	66.89
	✓	**86.79**	**83.60**	**59.66**	**42.89**	**46.17**	**52.45**	**74.07**
SWAV [11]		82.21	81.60	52.00	29.78	36.69	37.68	53.01
	✓	**82.57**	**82.00**	**55.10**	**33.16**	**39.13**	**40.74**	**61.69**

Object localization (blue is ground-truth & red is prediction)

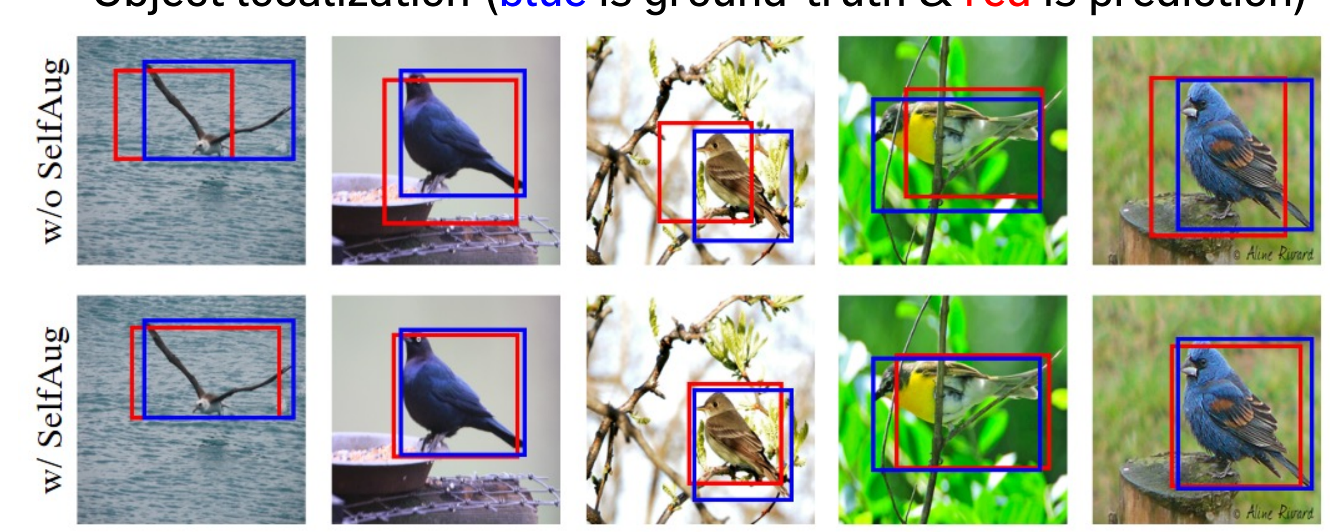


Image retrieval: SimSiam (left) vs SimSiam+AugSelf (right, ours)