A Simple Framework for Contrastive Learning of Visual Representations

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Problema

Aprendizaje efectivo de representaciones visuales sin supervisión

Generativo:
Computacionalmente costoso

Discriminativo:
Limitación de generalidad

SimCLR

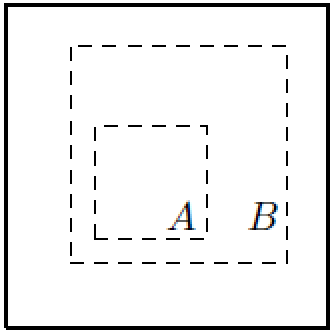
Aprendizaje basado en contraste

No requiere arquitectura especializada

No requiere banco de datos

Pilares

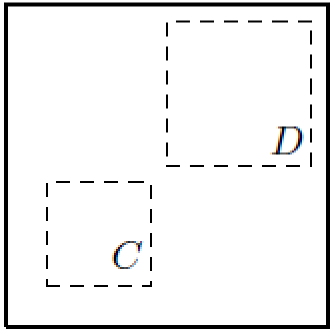
Data augmentation



Vista local y global

+

Random cropping y resizing



Vistas adyacentes

(a) Original

(b) Crop and resize

(c) Crop, resize (and flip)

(d) Color distort. (drop)

(e) Color distort. (jitter)

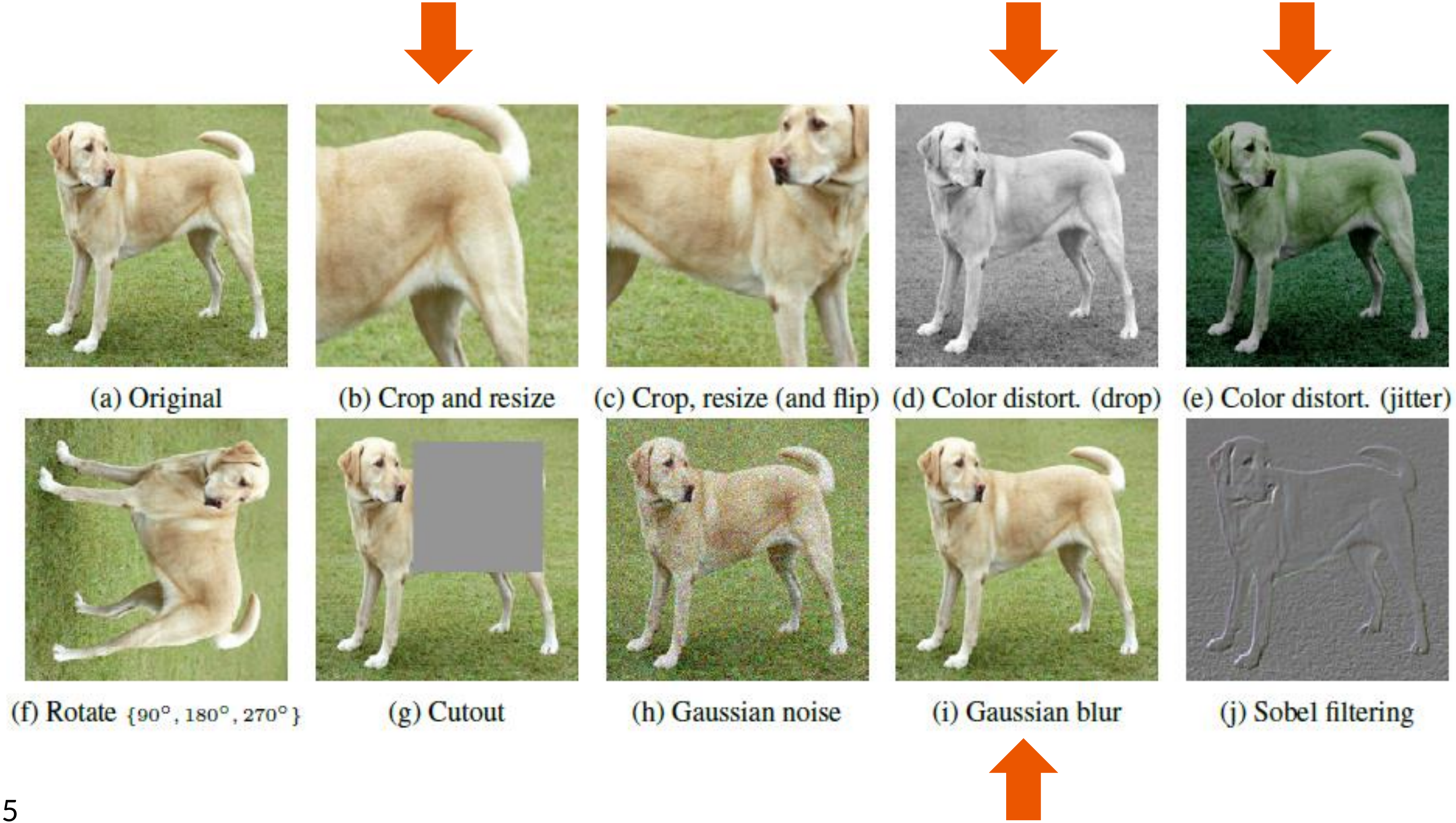
(f) Rotate $\{90°, 180°, 270°\}$

(g) Cutout

(h) Gaussian noise

(i) Gaussian blur

(j) Sobel filtering


(a) Original
(b) Crop and resize
(c) Crop, resize (and flip)
(d) Color distort. (drop)
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(f) Rotate {90°, 180°, 270°}
(g) Cutout
(h) Gaussian noise
(i) Gaussian blur
(j) Sobel filtering

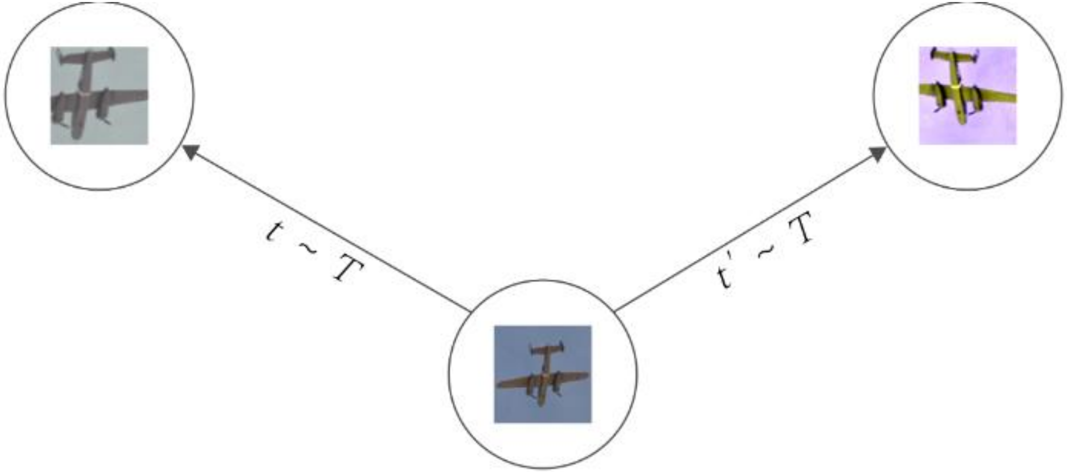
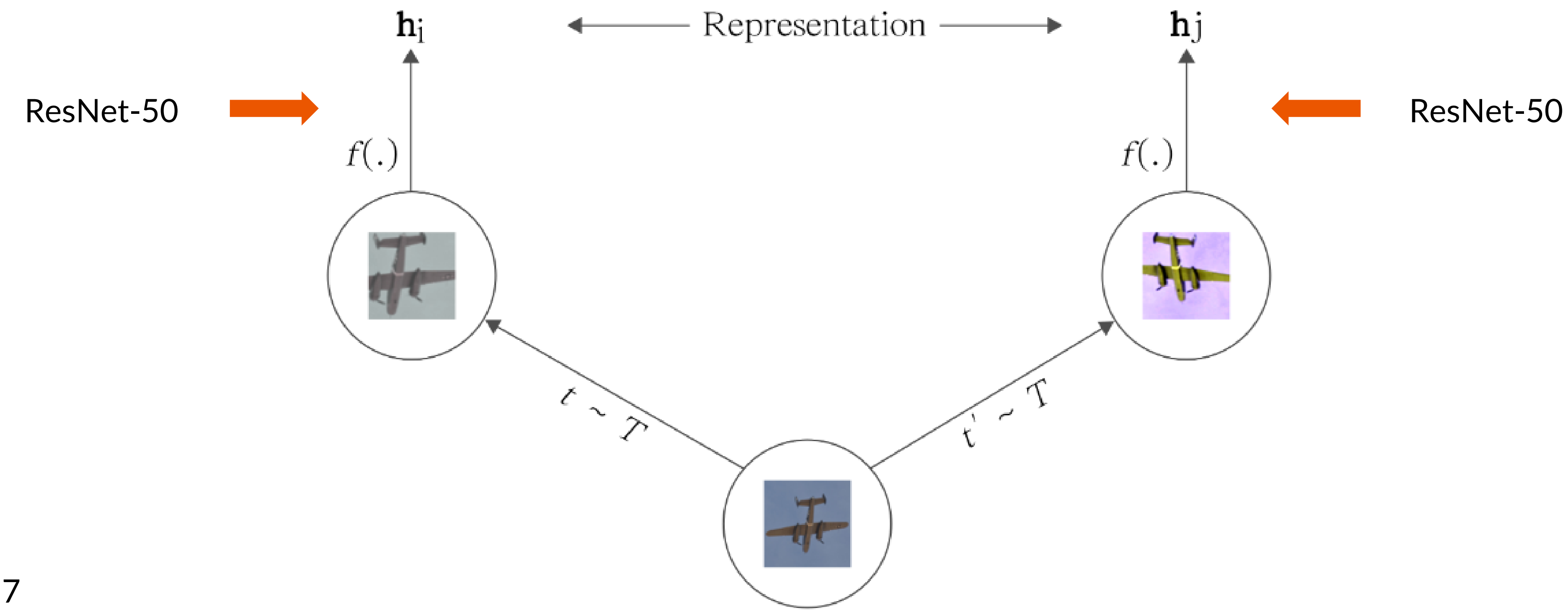


Imagen: https://github.com/sthalles/SimCLR

Neural Network Encoder ResNet



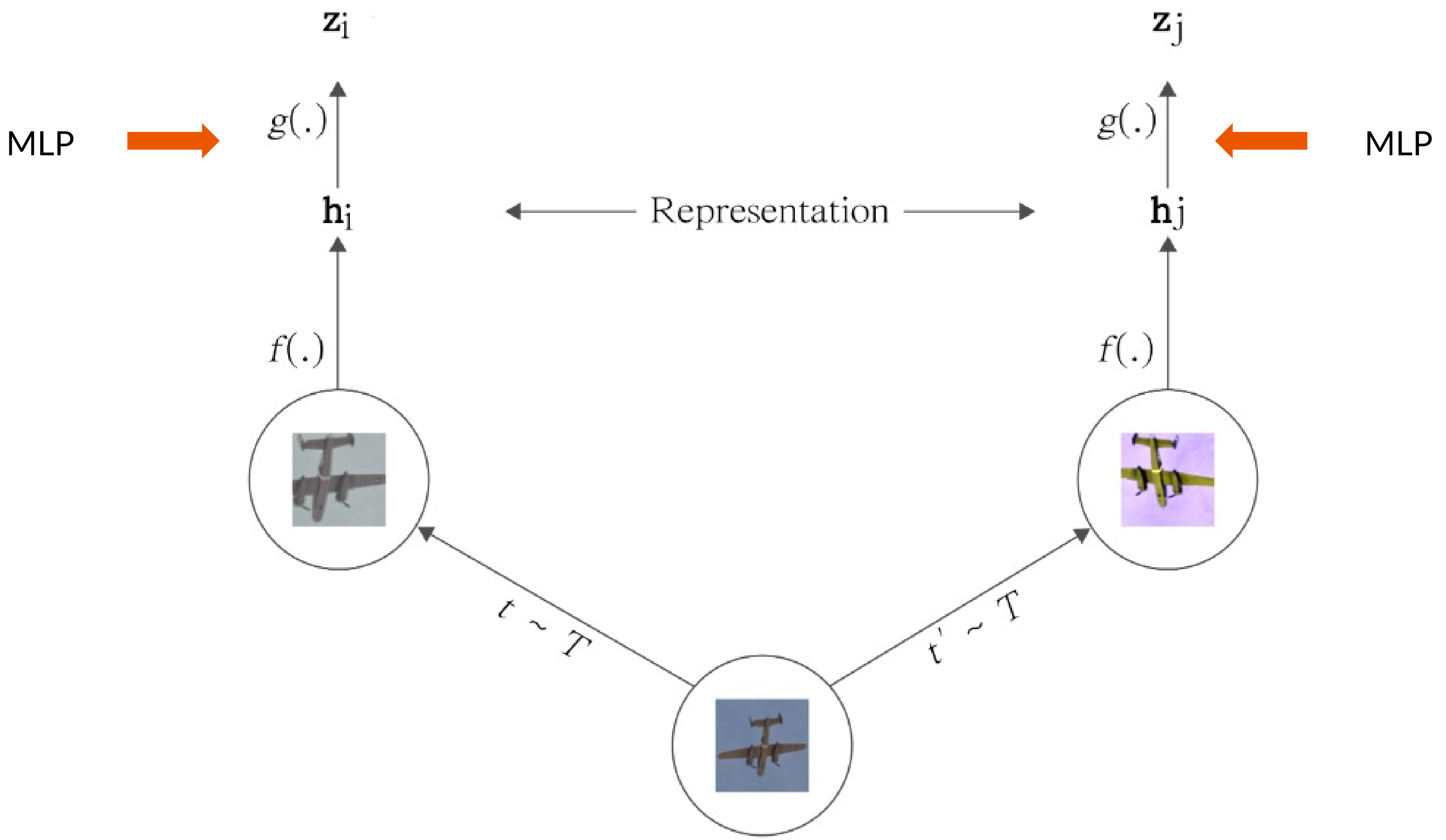
$\mathbf{h}_i$
Representation
$\mathbf{h}_j$
ResNet-50
ResNet-50
$f(.)$
$f(.)$
$t \sim T$
$t' \sim T$

Projection Head

MLP
1 hidden layer

$$\boldsymbol{z}_i = g(\boldsymbol{h}_i) = W^{(2)}\sigma(W^{(1)}\boldsymbol{h}_i)$$

ReLU



$\mathbf{z}_i$
$\mathbf{z}_j$
MLP
$g(.)$
$g(.)$
MLP
$\mathbf{h}_i$
Representation
$\mathbf{h}_j$
$f(.)$
$f(.)$
$t \sim T$
$t' \sim T$

Contrastive Loss Function

$$\ell_{i,j} = -\log \frac{\exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)}$$

$$\mathrm{sim}(\boldsymbol{u}, \boldsymbol{v}) = \boldsymbol{u}^\top \boldsymbol{v} / \|\boldsymbol{u}\| \|\boldsymbol{v}\|$$

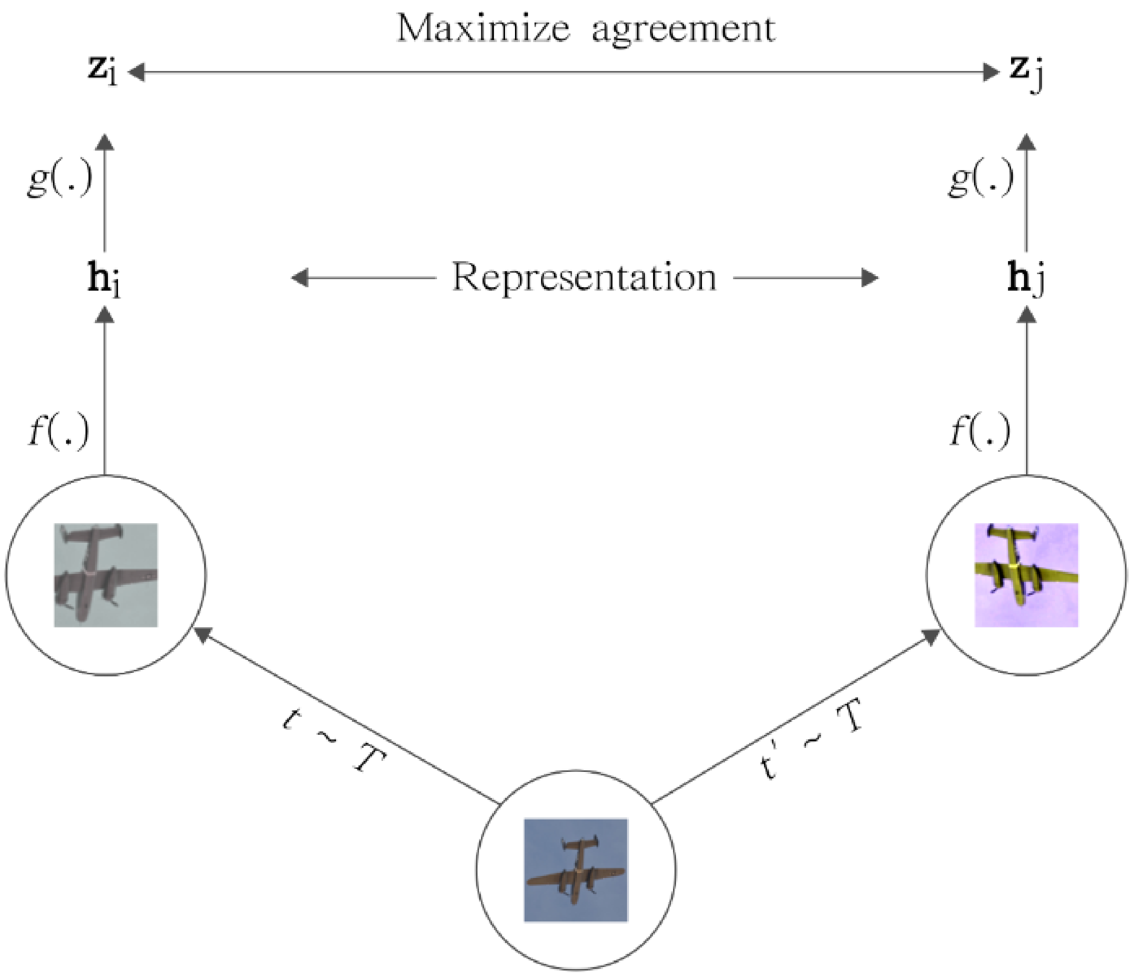
τ = Parámetro de temperatura

NT-Xent

(normalized temperature-scaled cross entropy loss)

Margin	NT-Logi.	Margin (sh)	NT-Logi.(sh)	NT-Xent
50.9	51.6	57.5	57.9	63.9

Table 4. Linear evaluation (top-1) for models trained with different loss functions. “sh” means using semi-hard negative mining.



Maximize agreement
$\mathbf{z}_i$
$\mathbf{z}_j$
$g(.)$
$g(.)$
$\mathbf{h}_i$
Representation
$\mathbf{h}_j$
$f(.)$
$f(.)$
$t \sim T$
$t' \sim T$

Entrenamiento por Batches

Batches de
256 a 8192

LARS
Estabilizar entrenamiento

Global BN
Normalizar datos

Resultados y Comparación

Evaluación Lineal

Method	Architecture	Param (M)	Top 1	Top 5
Methods using ResNet-50:				
Local Agg.	ResNet-50	24	60.2	-
MoCo	ResNet-50	24	60.6	-
PIRL	ResNet-50	24	63.6	-
CPC v2	ResNet-50	24	63.8	85.3
SimCLR (ours)	ResNet-50	24	**69.3**	**89.0**
Methods using other architectures:				
Rotation	RevNet-50 (4×)	86	55.4	-
BigBiGAN	RevNet-50 (4×)	86	61.3	81.9
AMDIM	Custom-ResNet	626	68.1	-
CMC	ResNet-50 (2×)	188	68.4	88.2
MoCo	ResNet-50 (4×)	375	68.6	-
CPC v2	ResNet-161 (∗)	305	71.5	90.1
SimCLR (ours)	ResNet-50 (2×)	94	74.2	92.0
SimCLR (ours)	ResNet-50 (4×)	375	**76.5**	**93.2**

Semi-supervisado

Method	Architecture	Label fraction 1%	10%
		Top 5	
Supervised baseline	ResNet-50	48.4	80.4
Methods using other label-propagation:			
Pseudo-label	ResNet-50	51.6	82.4
VAT+Entropy Min.	ResNet-50	47.0	83.4
UDA (w. RandAug)	ResNet-50	-	88.5
FixMatch (w. RandAug)	ResNet-50	-	89.1
S4L (Rot+VAT+En. M.)	ResNet-50 (4×)	-	91.2
Methods using representation learning only:			
InstDisc	ResNet-50	39.2	77.4
BigBiGAN	RevNet-50 (4×)	55.2	78.8
PIRL	ResNet-50	57.2	83.8
CPC v2	ResNet-161(∗)	77.9	91.2
SimCLR (ours)	ResNet-50	75.5	87.8
SimCLR (ours)	ResNet-50 (2×)	83.0	91.2
SimCLR (ours)	ResNet-50 (4×)	**85.8**	**92.6**

Transfer Learning

	Food	CIFAR10	CIFAR100	Birdsnap	SUN397	Cars	Aircraft	VOC2007	DTD	Pets	Caltech-101	Flowers
Linear evaluation:												
SimCLR (ours)	**76.9**	**95.3**	80.2	48.4	**65.9**	60.0	61.2	**84.2**	**78.9**	89.2	**93.9**	**95.0**
Supervised	75.2	**95.7**	**81.2**	**56.4**	64.9	**68.8**	**63.8**	83.8	**78.7**	**92.3**	**94.1**	94.2
Fine-tuned:												
SimCLR (ours)	**89.4**	**98.6**	**89.0**	**78.2**	**68.1**	**92.1**	**87.0**	**86.6**	**77.8**	92.1	**94.1**	97.6
Supervised	88.7	98.3	**88.7**	**77.8**	67.0	91.4	**88.0**	86.5	**78.8**	**93.2**	**94.2**	**98.0**
Random init	88.3	96.0	81.9	**77.0**	53.7	91.3	84.8	69.4	64.1	82.7	72.5	92.5

Cierre

- Arquitectura fácil de entender
- Buena respuesta al problema de aprendizaje de representaciones visuales sin supervisión
- Mejor que el estado del arte

Reseña

Anexo

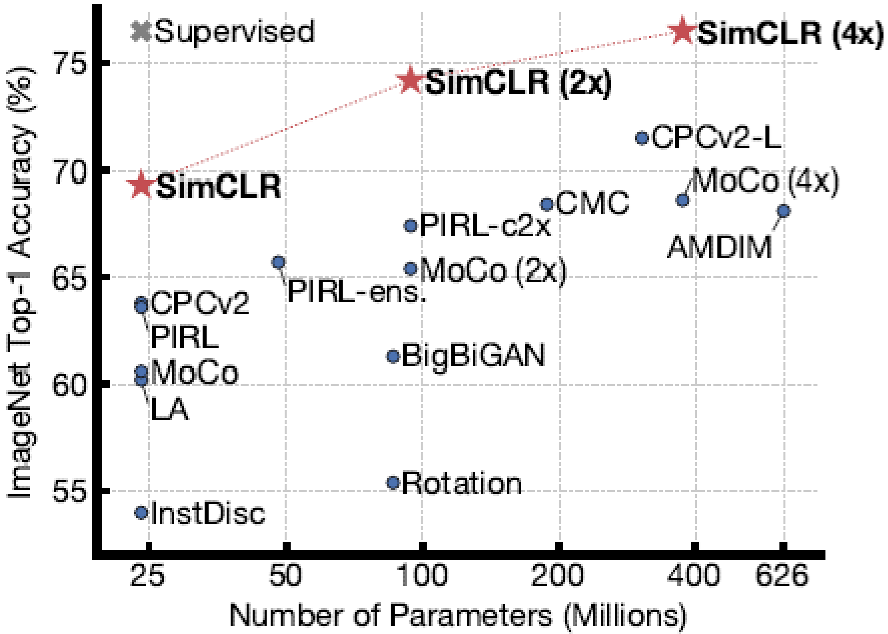


Figure 1. ImageNet Top-1 accuracy of linear classifiers trained on representations learned with different self-supervised methods (pretrained on ImageNet). Gray cross indicates supervised ResNet-50. Our method, SimCLR, is shown in bold.

Algorithm 1 SimCLR's main learning algorithm.

input: batch size N, constant τ, structure of f, g, $\mathcal{T}$.
for sampled minibatch $\{x_k\}_{k=1}^{N}$ **do**
  for all $k \in \{1, \ldots, N\}$ **do**
    draw two augmentation functions $t \sim \mathcal{T}, t' \sim \mathcal{T}$
    # the first augmentation
    $\tilde{\boldsymbol{x}}_{2k-1} = t(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k-1} = f(\tilde{\boldsymbol{x}}_{2k-1})$ # representation
    $\boldsymbol{z}_{2k-1} = g(\boldsymbol{h}_{2k-1})$ # projection
    # the second augmentation
    $\tilde{\boldsymbol{x}}_{2k} = t'(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k} = f(\tilde{\boldsymbol{x}}_{2k})$ # representation
    $\boldsymbol{z}_{2k} = g(\boldsymbol{h}_{2k})$ # projection
  end for
  for all $i \in \{1, \ldots, 2N\}$ and $j \in \{1, \ldots, 2N\}$ **do**
    $s_{i,j} = \boldsymbol{z}_i^\top \boldsymbol{z}_j / (\|\boldsymbol{z}_i\| \|\boldsymbol{z}_j\|)$ # pairwise similarity
  end for
  define $\ell(i,j)$ **as** $\ell(i,j) = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(s_{i,k}/\tau)}$
  $\mathcal{L} = \frac{1}{2N} \sum_{k=1}^{N} [\ell(2k-1, 2k) + \ell(2k, 2k-1)]$
  update networks f and g to minimize $\mathcal{L}$
end for
return encoder network $f(\cdot)$, and throw away $g(\cdot)$

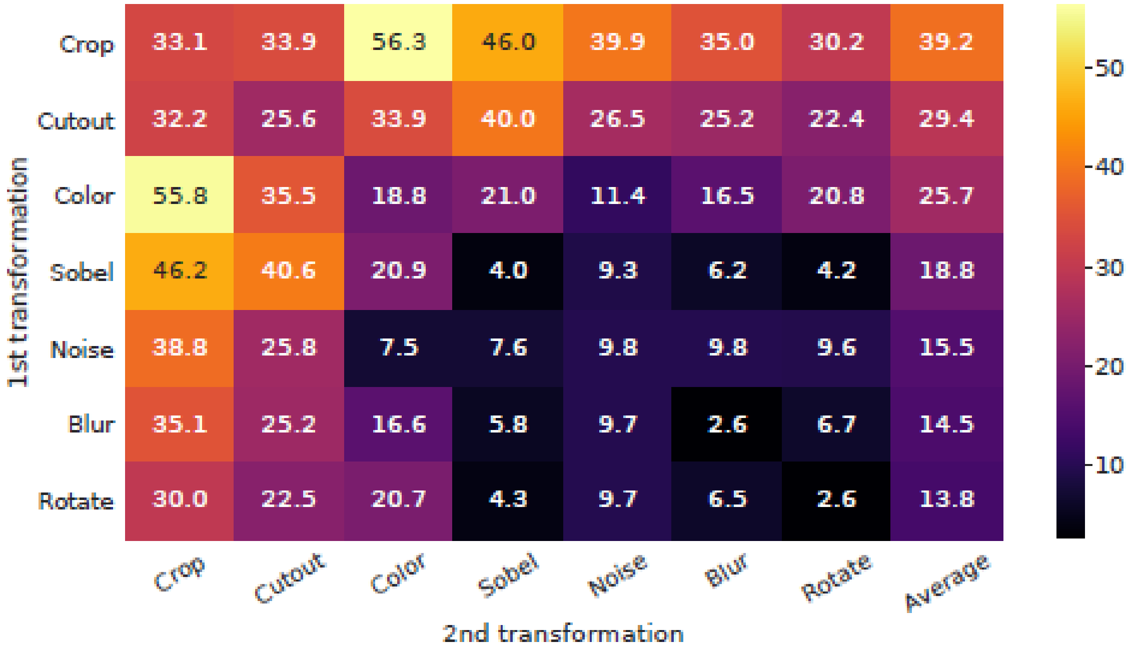


Figure 5. Linear evaluation (ImageNet top-1 accuracy) under individual or composition of data augmentations, applied only to one branch. For all columns but the last, diagonal entries correspond to single transformation, and off-diagonals correspond to composition of two transformations (applied sequentially).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

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

Table 3. Accuracy of training additional MLPs on different representations to predict the transformation applied. Other than crop and color augmentation, we additionally and independently add rotation (one of $\{0°, 90°, 180°, 270°\}$), Gaussian noise, and Sobel filtering transformation during the pretraining for the last three rows. Both h and $g(h)$ are of the same dimensionality, i.e. 2048.

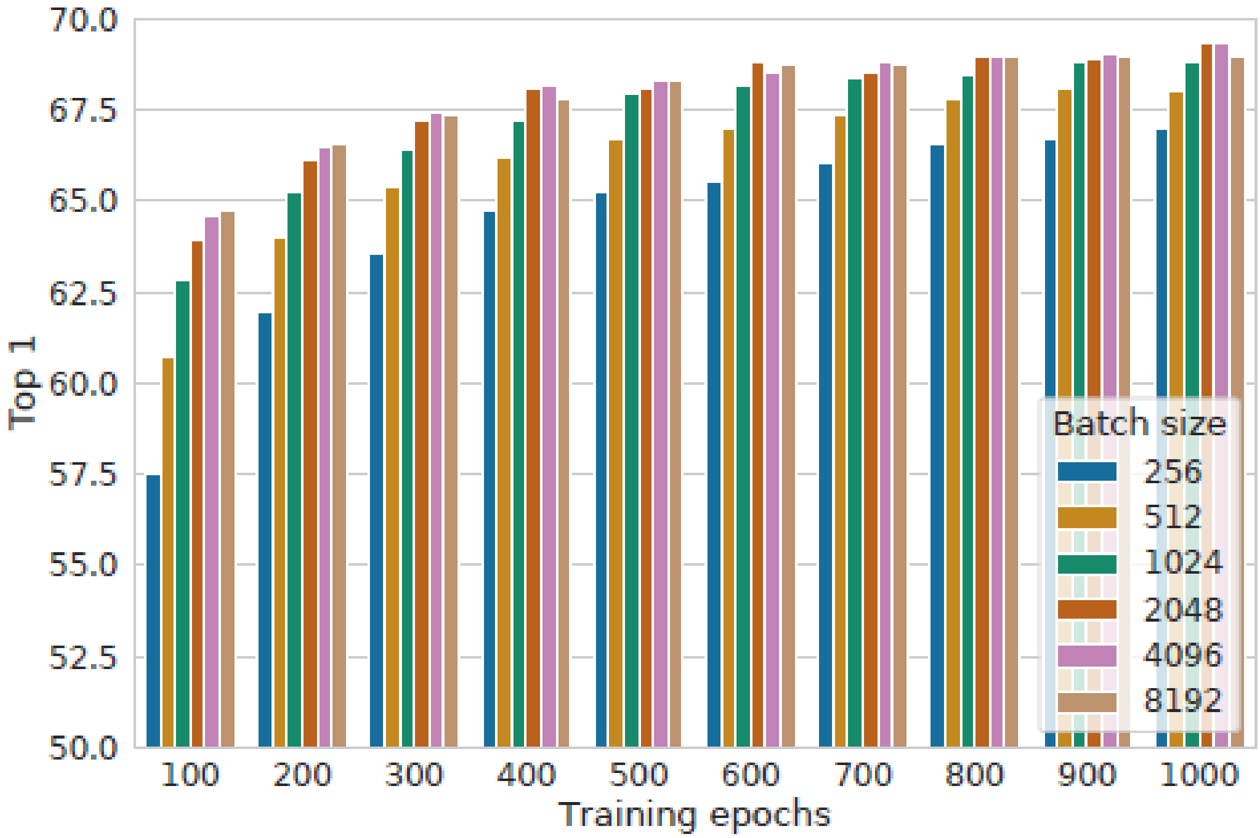


Figure 9. Linear evaluation models (ResNet-50) trained with different batch size and epochs. Each bar is a single run from scratch.[10]

Default setting. Unless otherwise specified, for data augmentation we use random crop and resize (with random flip), color distortions, and Gaussian blur (for details, see Appendix A). We use ResNet-50 as the base encoder network, and a 2-layer MLP projection head to project the representation to a 128-dimensional latent space. As the loss, we use NT-Xent, optimized using LARS with learning rate of 4.8 ($= 0.3 \times \mathrm{BatchSize}/256$) and weight decay of 10^{-6}. We train at batch size 4096 for 100 epochs.[3] Furthermore, we use linear warmup for the first 10 epochs, and decay the learning rate with the cosine decay schedule without restarts (Loshchilov & Hutter, 2016).