

When Does Self-Supervision Improve Few-Shot Learning?

Jong-Chyi Su, Subhransu Maji, Bharath Hariharan
ECCV 2020

<https://arxiv.org/pdf/1910.03560.pdf>

Outline

- Investigate the role of Self-Supervision Learning (SSL) in Few-Shot Learning (FSL)
- Findings
 - SSL improves the few-shot learner even when the datasets are **small** and **only** use images within the dataset
 - SSL can hurt when the distribution of images using for meta-learning and SSL are different
- Propose a simple approach to classify unlabeled data to pick data from similar domains

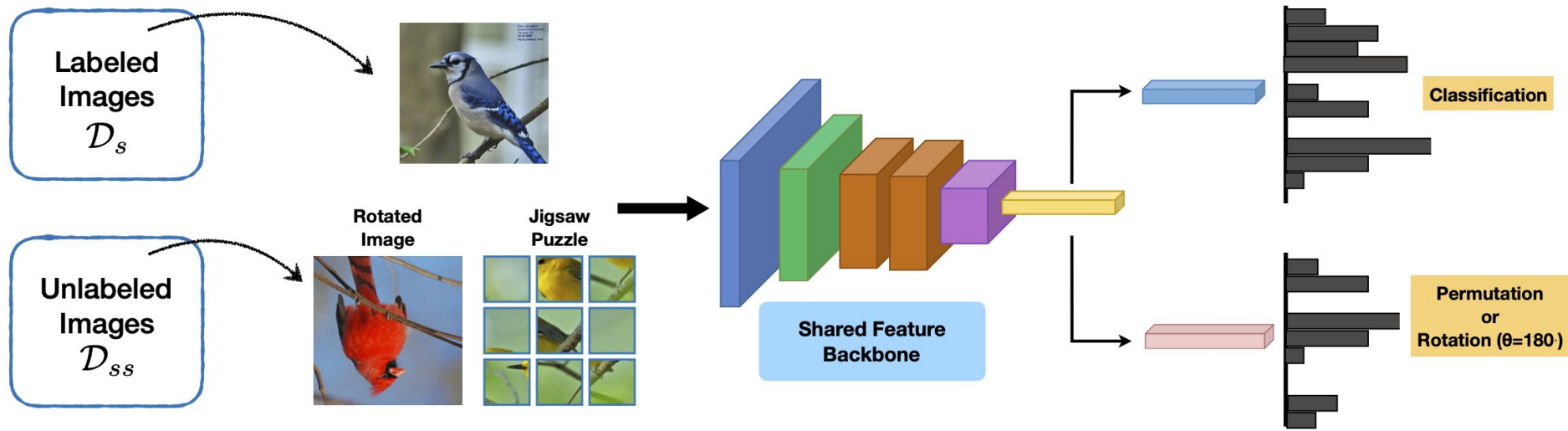


Fig. 1: **Combining supervised and self-supervised losses for few-shot learning.** Self-supervised tasks such as jigsaw puzzle or rotation prediction act as a data-dependent regularizer for the shared feature backbone. Our work investigates how the performance on the *target task domain* (\mathcal{D}_s) is impacted by the choice of the *domain used for self-supervision* (\mathcal{D}_{ss}).

Few-shot with Self-supervision

Few-shot loss

$$\mathcal{L}_s := \sum_{(x_i, y_i) \in \mathcal{D}_s} \ell(g \circ f(x_i), y_i) + \mathcal{R}(f, g).$$

Self-supervision loss

$$\mathcal{L}_{ss} := \sum_{x_i \in \mathcal{D}_{ss}} \ell(h \circ f(\hat{x}_i), \hat{y}_i).$$

Data: (x_i, y_i)

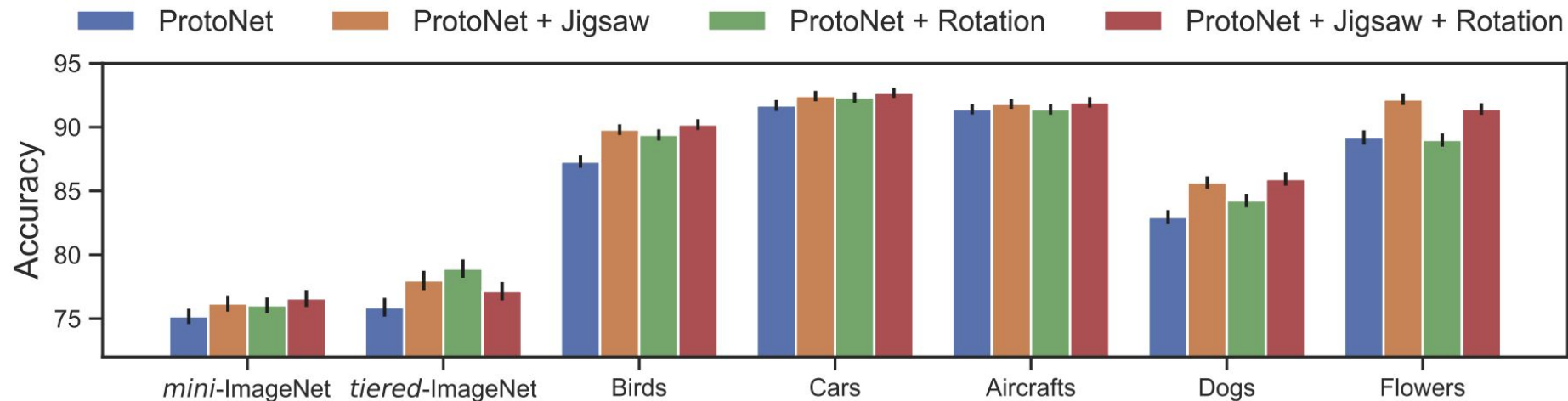
Augmented data: (\hat{x}_i, \hat{y}_i)

Encoder: f

FSL classifier: g

Self-supervision

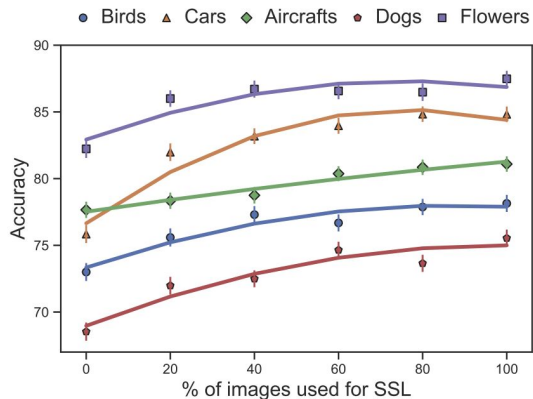
- Jigsaw puzzle task loss:
 - The input x is tiled into 3×3 regions, then permuted to obtain x_{hat}
 - The label y_{hat} is the index of the permutation.
 - The y_{hat} is then grouped by hamming distance to control the difficulty of the task
- Rotation task loss:
 - The image is rotated by angle of 0, 90, 180, 270 degree



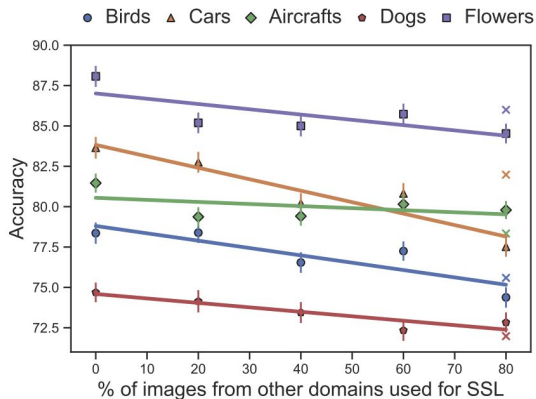
Loss	Birds	Cars	Aircrafts	Dogs	Flowers
	5-way 5-shot				
Softmax	81.5±0.5	87.7±0.5	89.2±0.4	77.6±0.6	91.0±0.5
Softmax + Jigsaw	83.9±0.5	90.6±0.5	89.6±0.4	77.8±0.6	91.1±0.5
MAML	81.2±0.7	86.9±0.6	88.8±0.5	77.3±0.7	79.0±0.9
MAML + Jigsaw	81.1±0.7	89.0±0.5	89.1±0.5	77.3±0.7	82.6±0.7
ProtoNet	87.3±0.5	91.7±0.4	91.4±0.4	83.0±0.6	89.2±0.6
ProtoNet + Jigsaw	89.8±0.4	92.4±0.4	91.8±0.4	85.7±0.5	92.2±0.4

Domain shift

- (a) SSL and FSL are trained on the same domain
- (b) SSL and FSL are trained on different domains



(a) Effect of number of images on SSL.



(b) Effect of domain shift on SSL.

Data selection for SSL

- Using a “domain weighted” model to select the top images based on a domain classifier.
- Binary classifier with positive sample from training set and negative from unlabeled data
-

- No SSL: FSL only on 20% dataset (lower bound)
- SSL 20% dataset: FSL + SSL on 20% dataset
- SSL pool random: randomly select from the pool
- SSL pool weight: using binary classifier
- Oracle: FSL on 20% and SSL on 100% dataset

