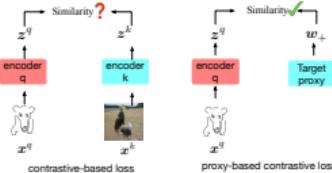


PCL: Proxy-based Contrastive Learning for Domain Generalization

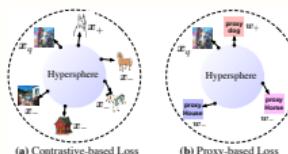
Xufeng Yao, Yang Bai, Xinyun Zhang, Yuechen ZHANG, QI SUN, Ran Chen, Ruiyu Li, Bei Yu. CUHK & SmartMore.

Background & Motivation



- ◆ Hard positive pairs may hamper DG
- ◆ Using Proxy to reduce the complexity of contrastive loss

Comparison between two losses



- ◆ **Contrastive loss:** sample-to-sample pairs
- ◆ **Proxy loss:** proxy-to-sample pairs

Complexity comparison

Loss function	positive pair	negative pair	relation	category	training complexity
softmax CE loss	(w_i, z_i)	$(w_1, z_1), (w_2, z_2), \dots, (w_n, z_n)$	proxy-to-sample	proxy-based	$\mathcal{O}(CN)$
Contrastive loss	(x_i, x_j)	$(x_1, x_1), (x_1, x_2), \dots, (x_1, x_n)$	sample-to-sample	pair-based	$\mathcal{O}(N^2)$
MS Loss	$(x_1, x_2) \dots (x_1, x_n)$	$(x_1, x_1), (x_2, x_2), \dots (x_1, x_n)$	sample-to-sample	pair-based	$\mathcal{O}(N^2)$
triplet Loss	$(x_1, x_2) \dots (x_1, x_n)$	$(x_1, x_1), (x_1, x_2) \dots (x_1, x_n)$	sample-to-sample	pair-based	$\mathcal{O}(N^3)$

- ◆ **Pair-based loss:** rich sample-to-sample pairs, high complexity
- ◆ **Proxy-based loss:** low complexity, high generalization

Proxy-based Contrastive Learning

Review Softmax-based CE Loss

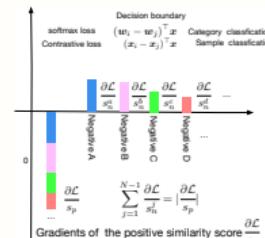
- ◆ **Advantage:** learn a proxy for each class efficiently
- ◆ **Disadvantage:** miss rich sample-to-sample pairs

Review Contrastive-based Loss

- ◆ **Advantage:** plentiful sample-to-sample pairs, implicit hard pair mining

$$\begin{aligned} \mathcal{L}_{\text{CL}} &= \lim_{\alpha \rightarrow \infty} \frac{1}{\alpha} - \log \left(\frac{\exp(\alpha \cdot s_p)}{\exp(\alpha \cdot s_p) + \sum_{j=1}^{N-1} \exp(\alpha \cdot s_n^j)} \right) \\ &= \lim_{\alpha \rightarrow \infty} \frac{1}{\alpha} \log \left(1 + \sum_{j=1}^{N-1} \exp(\alpha \cdot s_n^j - s_p) \right) \\ &= \max[s_n^j - s_p] + . \end{aligned}$$

- ◆ **Disadvantage:** high complexity, hard to optimize



Our Solution Combine softmax and contrastive losses

$$\mathcal{L}_{\text{PCL}} = -\frac{1}{N} \sum_{i=1}^N \log \frac{\exp(\mathbf{w}_c^\top \mathbf{z}_i \cdot \alpha)}{Z}$$

where Z is given by:

$$Z = \exp(\mathbf{w}_c^\top \mathbf{z}_i \cdot \alpha) + \sum_{k=1}^{C-1} \exp(\mathbf{w}_k^\top \mathbf{z}_i \cdot \alpha) + \sum_{j=1, j \neq i}^K \exp(\mathbf{z}_i^\top \mathbf{z}_j \cdot \alpha)$$

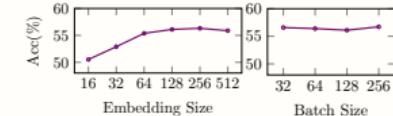
Results

Ablation study on positive loss

Method	PACS	OfficeHome	TerrIncognita
softmax CE	68.1	70.6	50.0
softmax CE w. positive loss	66.7	70.1	48.5

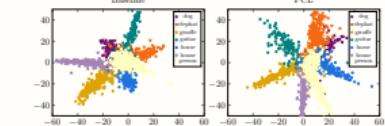
Positive loss is not effective in DG

Ablation study on different settings

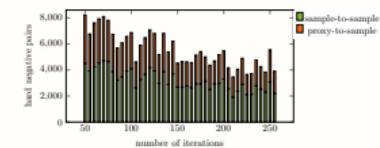


Our method is relative stable with different setting

t-SNE visualization results



Analysis on hard negative pairs selection



Good selection of hard negative pairs

Results

Algorithm	A	C	P	R	Avg
Mixstyle	51.1	53.2	68.2	69.2	60.4
ERM	63.1	51.9	77.2	78.1	67.6
I-Mixup	62.4	54.8	76.9	78.3	68.1
SagNet	63.4	54.8	75.8	75.3	68.1
CORAL	65.3	54.4	76.5	78.4	68.7
SWAD	66.1	57.7	78.4	80.2	70.6
Ours	67.3	59.9	78.7	80.7	71.6

Our method achieves the **sota** performance on several benchmarks, e.g., OfficeHome.