Hyperspherical Consistency Regularization

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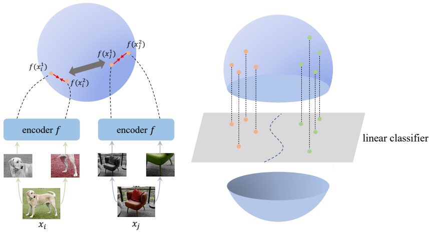
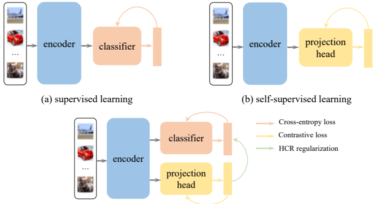
Section 1 Contrastive learning on the hypersphere

- Contrastive learning usually projects feature embeddings on a hypersphere while maximizing distances between negative pairs and minimizing distances between positive pairs.
- Linear classifier learns to separate the hypersphere through the hyperplane.

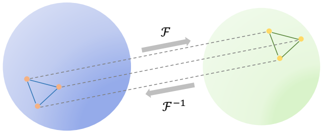


Section 2 Hypersphere consistency regularization

- Conceptual illustration of different learning paradigms.
- Supervised learning and self-supervised learning learn proper representations through different pretext tasks relying on label-dependent and feature-dependent information respectively.
- HCR takes supervised learning as the primary task and forces self-supervised learning to assist it from another perspective.



(a) supervised learning
(b) self-supervised learning
(c) learning with HCR



projection head's hypersphere
classifier's hypersphere

- Define the objective of HCR:

$$HCR\left(p(d_g), q(d_h)\right) = -p(d_g)\log\left(q(d_h)\right) - (1 - p(d_g))\log(1 - q(d_h))$$

where,

$$p(d_g) = C_g \frac{1}{\sigma_g\sqrt{2\pi}} \exp\left[-\frac{1}{2}\frac{(d_g-\mu_g)^2}{\sigma_g^2}\right]$$

$$q(d_h) = C_h \frac{1}{\sigma_h\sqrt{2\pi}} \exp\left[-\frac{1}{2}\frac{(d_h-\mu_h)^2}{\sigma_h^2}\right]$$

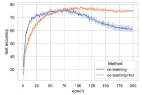
Section 3 Experimental results

- For semi-supervised learning on Stanford Cars, HCR significantly improves the performance of Self-Tuning by an average of 2.30% in different label proportions.
- In fine-grained classification, HCR performs consistently better than the baselines.
- For noisy label learning on CIFAR-100 with symmetric noises, HCR further improves Co-learning by averagely 3.92% under different noise ratios.

Method	Label Proportion 15%	30%	50%
Pseudo-Labeling	40.93±0.23	67.02±0.19	78.71±0.30
Π-model	45.19±0.21	57.29±0.26	64.18±0.29
Mean Teacher	54.28±0.14	66.02±0.21	74.24±0.23
UDA	39.90±0.43	64.16±0.40	71.86±0.56
FixMatch	49.86±0.27	77.54±0.29	84.78±0.33
SimCLRv2	45.74±0.16	61.70±0.18	77.49±0.24
Self-Tuning	74.99±0.11	85.87±0.04	89.83±0.01
Self-Tuning+HCR	**78.76**±0.08	**87.70**±0.07	**91.14**±0.06

Method	Stanford Cars	Aircraft	CUB200
Fine-Tuning	87.20±0.19	81.13±0.21	78.01±0.16
L^2-SP	86.58±0.26	80.98±0.29	78.44±0.17
DELTA	86.32±0.20	80.44±0.20	78.63±0.18
BSS	87.63±0.27	81.48±0.18	78.85±0.31
Co-Tuning	89.53±0.09	83.87±0.09	81.24±0.14
Self-Tuning	92.33±0.10	88.96±0.21	81.60±0.11
Self-Tuning+HCR	**93.03**±0.06	**90.41**±0.03	**82.63**±0.19

Method	sym-20%	sym-50%	sym-80%
Standrad CE	57.79±0.44	33.75±0.46	8.64±0.22
Decoupling	56.18±0.32	31.58±0.54	7.71±0.23
Co-teaching	64.28±0.32	32.62±0.51	6.65±0.71
Co-teaching+	55.40±0.71	26.49±0.45	8.57±1.55
JoCoR	62.29±0.71	30.19±0.60	6.84±0.92
Co-learning	66.58±0.15	55.54±0.43	35.45±0.79
Co-learning+HCR	**70.27**±0.32	**59.93**± 0.25	**39.14**±0.47



- More experiments can be found in our paper.

Summary

- We propose hyperspherical consistency regularization (HCR), to encourage the pairwise distance distribution of the classifier to be similar to the distribution of the projection head in the latent space.
- Through extensive experiments on semi-supervised learning, fine-grained classification and noisy label learning, HCR shows consistent improvements on these tasks.