Learning to Generalize Unseen Domains via Memory-based Multi-Source Meta-Learning for Person Re-Identification (Supplementary Material)

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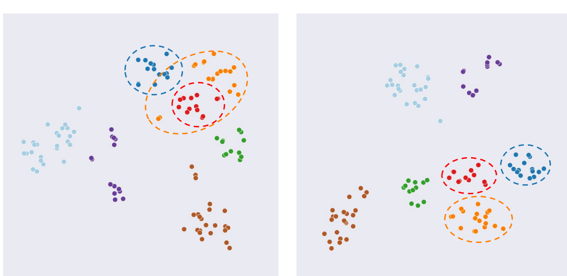
A. Visualization of the target domain

To better understand the advantage of the meta-learning strategy, we visualize the distributions of the inference features of the target domain (Market-1501 testing set) in Fig. A. Both baseline and M^3L are trained with DukeMTMC-reID, CUHK03, and MSMT17, and the inference features are obtained by 7 persons in the Market-1501 testing set. We use t-SNE [3] to reduce the features into a 2-D space. Different colors denote different identities. As shown in Fig. A, compared with the baseline, our M^3L pushes the features of the same identity more compact and pull the features of different identities more discriminating. This suggests that the proposed M^3L leads the model to learn more generalizable representations that can perform well on unseen domains.



(a) Baseline (b) M^3L

Figure A: t-SNE [3] visualization of 7 persons in the unseen target dataset (Market-1501 testing set). The color indicates the identity. Results are evaluated on (a) baseline and (b) M^3L, both of which are trained with ResNet-50.

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Table A: Results on different number of training IDs (the improvement in red).

Loss	Meta	#training IDs (D+MS+C→M) Rank-1 accuracy 50	100	500	1,000	3,110
$\mathcal{L}_{FCG}$	×	27.1	35.2	48.5	54.5	67.0
	✓	**30.2** (**3.1**)	**37.3** (**2.1**)	49.0 (0.5)	55.3 (0.8)	68.3 (1.3)
$\mathcal{L}_{FCP}$	×	27.1	35.2	48.5	54.5	67.0
	✓	28.7 (1.6)	36.8 (1.6)	49.4 (0.9)	55.9 (1.4)	69.3 (2.3)
$\mathcal{L}_{M}$	×	27.6	34.6	51.6	59.6	67.9
	✓	28.0 (0.4)	35.3 (0.7)	**53.8** (**2.2**)	**63.4** (**3.8**)	**74.5** (**6.6**)

B. Detailed comparison of different classifiers

Meta-learning is effective with the FC-based classifiers in many tasks, *e.g.,* few-shot learning [1, 2]. However, we found that the advantage of meta-learning with the FC-based classifiers will be degraded when the number of classes (IDs) is large. In Table A, we compare the results of three kinds of classifiers with different number of training IDs (#training IDs). With fewer IDs, the FC-based classifiers achieve higher improvement. However, with the increase of IDs, the memory-based classifier gains higher improvement. Hence, we conclude that the FC-based classifiers are not suitable for meta-learning when the the number of classes is large. Thus, the large number of IDs in ReID leads the FC-based classifiers to produce inferior improvements than the memory-based classifier with meta-learning.

References

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