

Supplementary Material for "Dual-Refinement: Joint Label and Feature Refinement for Unsupervised Domain Adaptive Person Re-Identification"

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A OVERALL TRAINING PROCEDURE

Algorithm 1: Alternative Training Procedure of Our Dual-Refinement Method

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Input: Labeled source dataset  $D_s$ ; Unlabeled target dataset  $D$  with  $N$  images; Feature encoder  $F$  pretrained on ImageNet; Identity classifier  $\phi$ ; Instant memory bank  $V$ ; Maximum training epoch  $max\_epoch$ ; Maximum training iteration  $max\_iter$   
Output: Optimized feature encoder  $F$  for target domain;  
1 Pretain feature encoder  $F$  on the labeled source dataset  $D_s$  with classification loss and triplet loss;  
2 for  $epoch = 1$  to  $max\_epoch$  do  
3   // Off-line pseudo label generation and refinement  
4   Extract features of the target dataset  $D$  using  $F$  and calculate Jaccard distance  $d_J(i, j)$  by Eq. (1) (2);  
5   Perform DBSCAN clustering on  $D$  with  $d_J$  and assign the coarse pseudo labels  $\tilde{D} = \{(x_i, \tilde{y}_i) |_{i=1}^N\}$ ;  
6   Perform fine clustering and assign refined pseudo labels by Eq. (6) (7) to obtain the refined target dataset  $\hat{D} = \{(x_i, \hat{y}_i) |_{i=1}^N\}$ ;  
7   // On-line feature learning and refinement  
8   for  $iter = 1$  to  $max\_iter$  do  
9     Sample  $(x_i, \tilde{y}_i, \hat{y}_i)$  from  $\tilde{D} \cup \hat{D}$ ;  
10    Update the feature encoder  $F$ , classifier  $\phi$  and instant memory bank  $V$  by computing the gradients of the overall loss (Eq. (12)) with back-propagation;  
11  end  
12 end  
13 return feature encoder  $F$ ;
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We demonstrate the details of the alternative training procedure for our Dual-Refinement method in Algorithm 1. Our method can be easily incorporated into the general clustering-based UDA framework [4]. In detail, we perform the DBSCAN clustering [1] by the implementation in scikit-learn [3].

B COMPUTATIONAL COST COMPARISONS

As shown in Table 1, we compare our Dual-Refinement method with the baseline and the state-of-the-art method MMT [2] in the computational cost. The experiments are conducted when Market1501 [5] \rightarrow DukeMTMC-ReID [6]. MMT uses two networks to train with each other, which is not memory efficient. Compared with MMT, our Dual-Refinement can achieve higher performance by costing less training time and GPU memory. Compared with the baseline method, our Dual-Refinement only introduces little extra GPU

Table 1: Computational cost comparisons.

Method	Market1501 \rightarrow DukeMTMC-ReID		
	R1 (%)	Time (hours)	GPU Memory (MB)
Baseline	72.5	3.17	8692
Dual-Refinement	82.1	3.53	9600
MMT	78.0	11.45	15068

memory cost (about 908 MB) and little extra time cost (about 0.36 hours) because of the proposed instant memory bank. However, our Dual-Refinement outperforms the baseline method’s rank-1 accuracy (R1) by a large margin. Based on the above analyses, our proposed Dual-Refinement is superior not only in the performance but also in the computational cost.

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