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Deep Domain Knowledge Distillation for Person Re-identification

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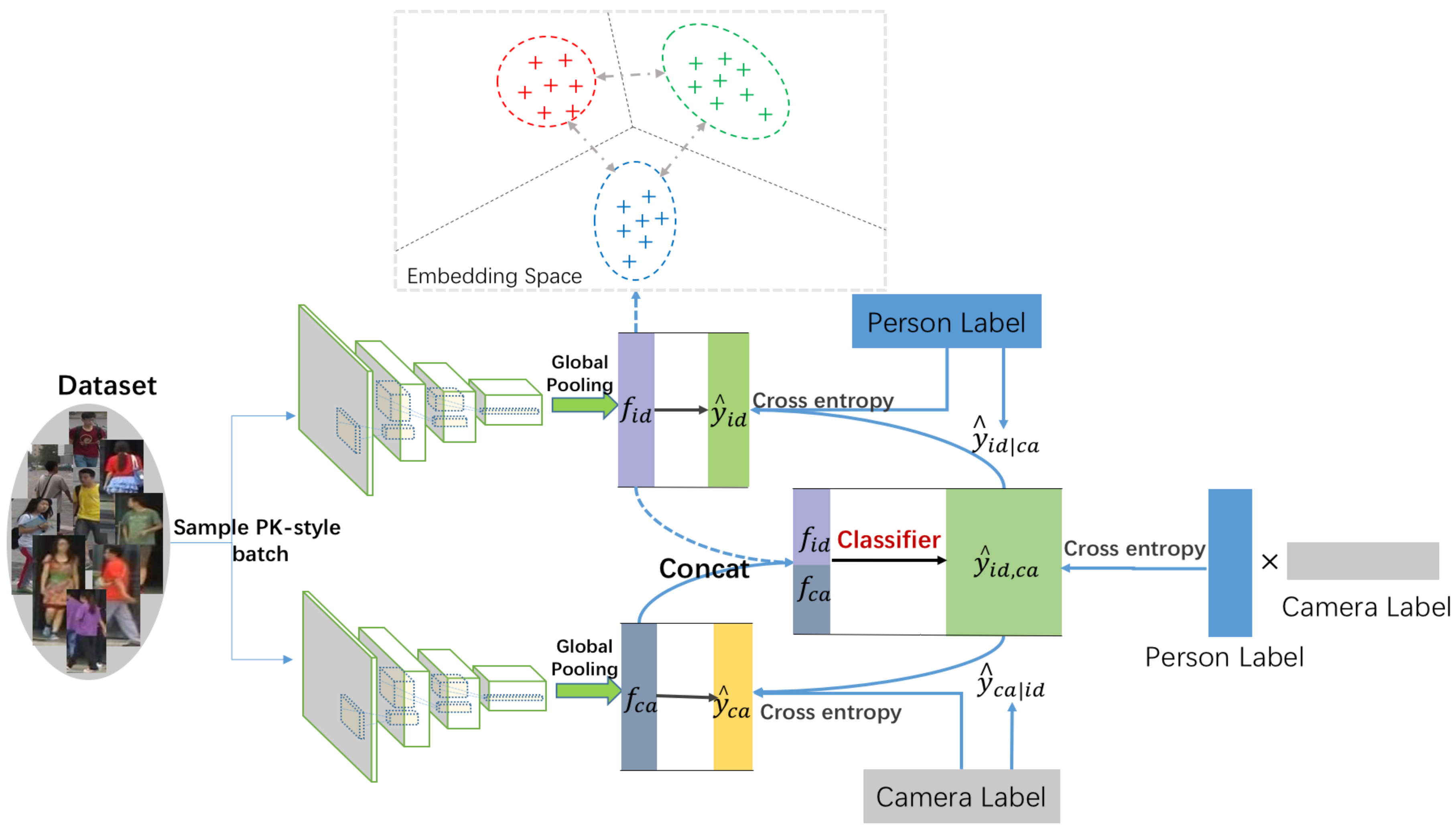
Abstracts

Learning generic and robust representations with data from multiple domains is a big challenge in Person ReID. In this paper, we propose an end-to-end framework called Deep Domain Knowledge Distil- lation (D2KD) for leaning more generic and robust features with Convo- lutional Neural Networks (CNNs). Domain-specific knowledge learned by the auxiliary network is transferred to the domain-free subnetwork and guides the optimization of the feature extractor. While person identity information is transferred to the auxiliary network to further accurately identify domain classes. In the test period, just with a single base model as the feature extractor, we improve the Rank-1 and mAP by a clear margin. Experiments on Market-1501, CUHK03 and DukeMTMC-reID demonstrate the effectiveness of our method.

Market1501 DukeMTMC-reID

Methods



- Triplet Loss

$$L_{tri\_batch}(\theta;B)=\sum_{a=1}^{B=PK}\Big[m+\max_{\substack{p=1\ldots B\\ y_p=y_a}}\mathcal{D}(f_a,f_p)-\min_{\substack{n=1\ldots B\\ y_n\neq y_a}}\mathcal{D}(f_a,f_n)\Big]_+$$

- KD Loss

$$L_{KD}=\frac{1}{n}\sum_{i=1}^{n}[H(\hat{y}_{id}(x_i),P(id|ca=y_{ca}(x_i),x_i))+H(\hat{y}_{ca}(x_i),P(ca|id=y_{id}(x_i),x_i))]$$

- Total Loss

$$L_{total}=L_{xent}+\lambda_1 L_{tri}+\lambda_2 L_{KD}$$

Experiment Results

Table 2. Comparison of several methods on Market-1501. Rank-1, Rank-5 and mAP are shown. We use ResNet-50 as backbone. '-': No reported result available

Methods	Rank-1	Rank-5	mAP
BoW + KISSME [23]	44.4	63.9	20.8
LOMO + Null Space [22]	55.43	-	29.87
Gated siamese CNN [18]	65.88	-	39.55
CAN [13]	60.3	-	35.9
ResNet 50(I+V) [25]	79.51	90.91	59.87
Latent Parts(Fusion) [10]	80.31	-	57.53
IDE(R)(Re-ranked) [28]	74.85	-	59.87
MultiScale [3]	88.9	-	73.1
TriNet [6]	84.92	94.21	69.14
TriNet [6] (Re-ranked)	86.67	93.38	81.07
AACN [20]	85.90	-	66.87
AACN [20] (Re-ranked)	88.69	-	82.96
PSE [15]	87.7	-	69.0
PSE [15] (Re-ranked)	90.2	-	83.5
D^2KD	**91.09**	97.03	**76.76**
D^2KD(Re-ranked)	**92.73**	96.11	**88.93**

Table 3. Comparison of several methods on CUHK03. Rank-1 accuracy (%) and mAP (%) are shown. We apply the new evaluation protocol on the CUHK03 proposed in [28]. We use ResNet-50 as backbone.

Methods	CUHK03		DukeMTMC-reID	
	Rank-1	mAP	Rank-1	mAP
BoW + KISSME [23]	6.4	6.4	25.1	12.2
LOMO + XQDA [12]	12.8	11.5	30.8	17.0
IDE [24]	21.3	19.7	65.2	45.0
PAN [26]	36.3	34.0	71.6	51.5
MultiScale [3]	40.7	37.0	79.2	60.6
SVDNet [16]	41.5	37.2	76.7	56.8
TriNet [6]	50.5	46.5	72.4	53.5
D^2KD	**60.9**	**56.3**	**80.5**	**64.1**

Table 4. Comparison of our D^2KD method to label smoothing (LS)

Methods	Rank-1
TriNet	88.0
TriNet + CE	89.3
TriNet + LS	89.8
D^2KD	91.1

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