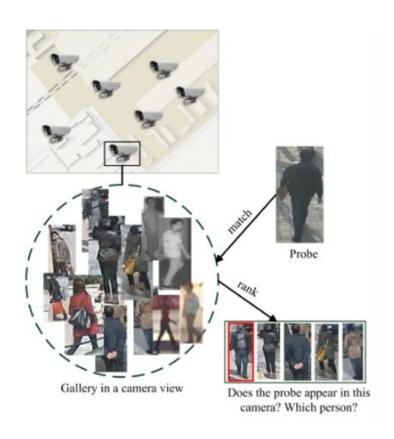
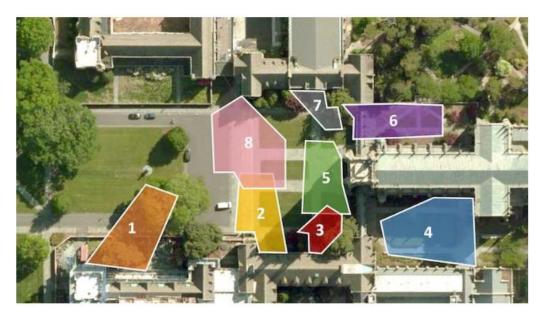
Unsupervised Domain Adaptation for open-set person re-identification

Huixiang Luo

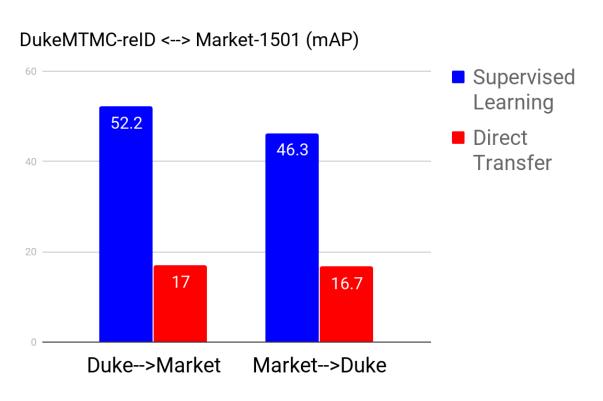
person re-identification





layout of the cameras in the DukeMTMC dataset

problem of domain shifts



create new dataset?

prohibitive manual effort for annotation

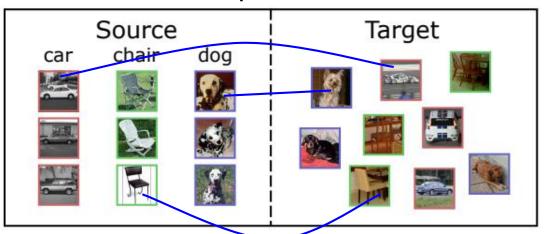


- 2. time-consuming
- 3. hard to reuse
- 4. privacy

transfer learning/ [domain adaptation

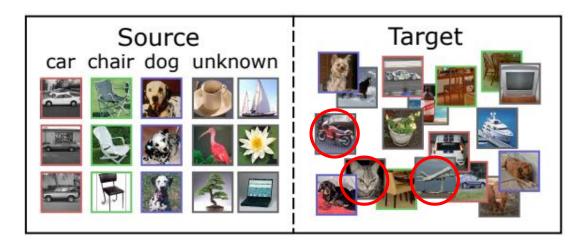
Unsupervised Domain Adaptation for closed-/open-set scenarios

close-set assumption: source and target domains share the same classes

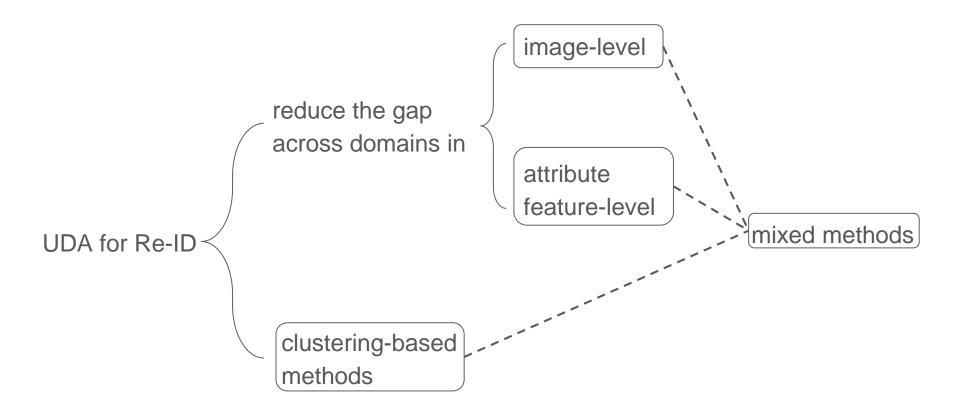


open-set assumption: classes from 2 domains are different

→ re-ID scenario



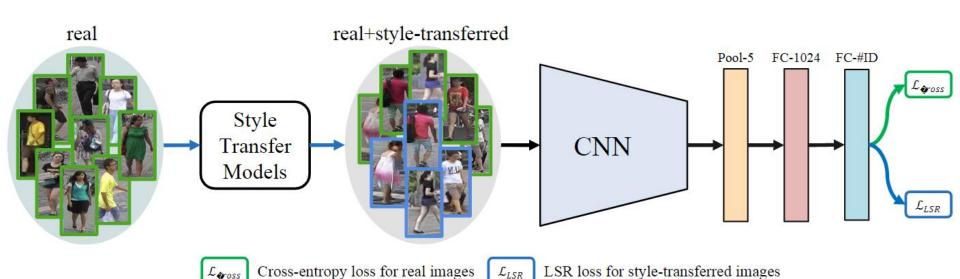
Current methods of UDA for open-set re-ID



1.reduce the gap across domains on the image-level

image-level gap SPGAN[CVPR 18], HHL methods [ECCV 18], PTGAN[CVPR 18]
reduction

CamStyle[TIP 19], ATNet[CVPR 19]

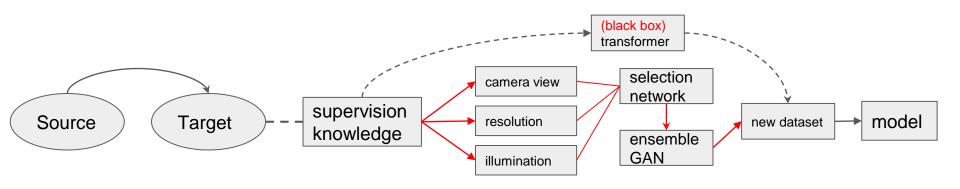


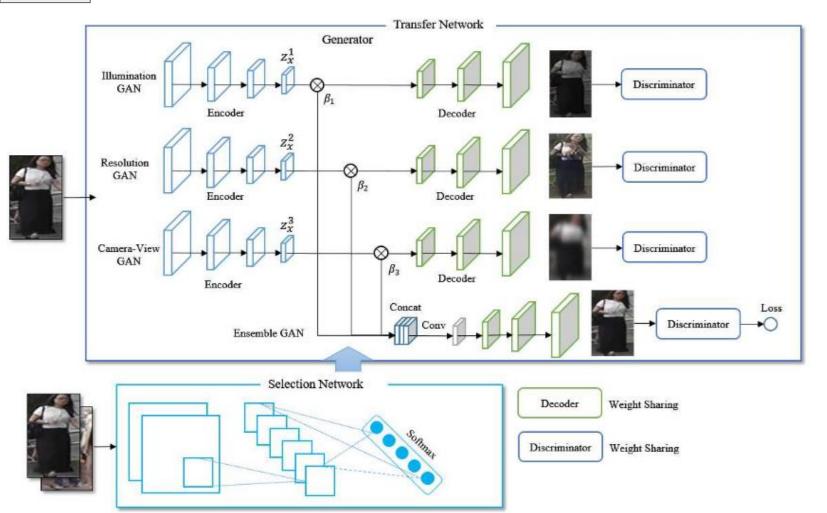
Adaptative Transfer Network for Cross-Domain Person Re-Identification (CVPR 2019)

What are the main factors of DA for re-id?

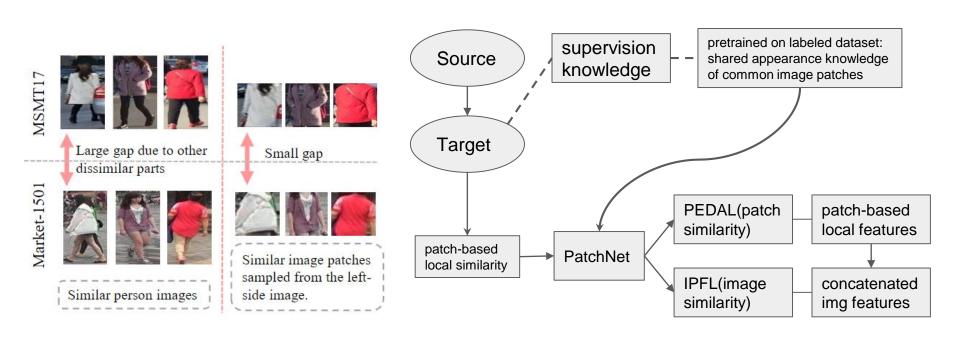
- Illumination
- Resolution
- Camera view

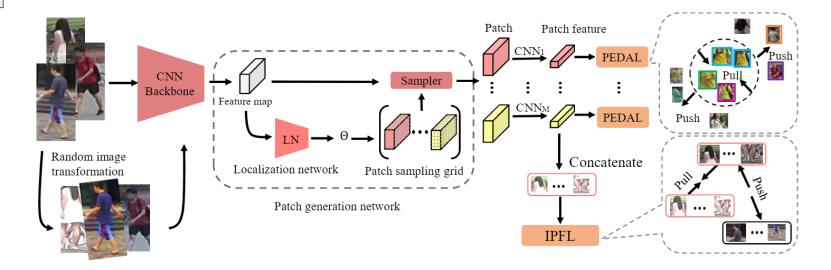




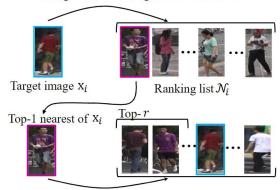


Patch-based Discriminative Feature Learning for Unsupervised Person Re-identification (CVPR 2019)





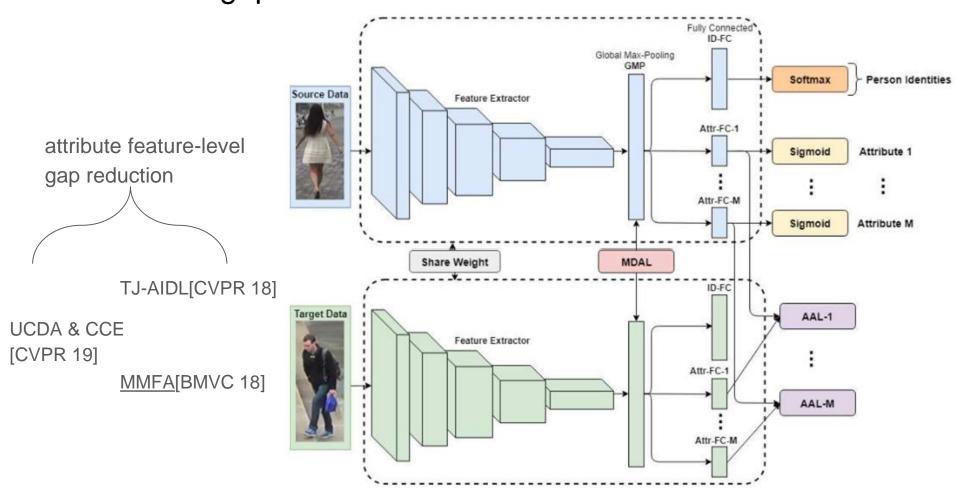
Ranking with other images in a mini-batch



Ranking with other images in a mini-batch

Source	DukeMT	MC-reID	Market-1501		
Target	Marke	t-1501	DukeMTMC-reII		
Methods	Rank-1	mAP	Rank-1	mAP	
PUL [7]	45.5 20.5		30.0	16.4	
PTGAN [40]	38.6	-	27.4	-	
TJ-AIDL [37]	58.2	26.5	44.3	23.0	
HHL [55]	62.2	31.4	46.9	27.2	
PAUL (Ours)	66.7	36.8	56.1	35.7	

2.reduce the gap across domains on the attribute feature-level

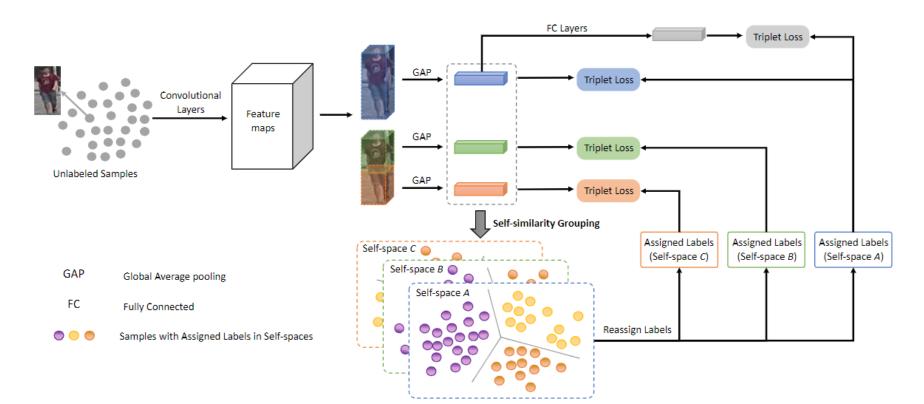


3.clustering-based methods

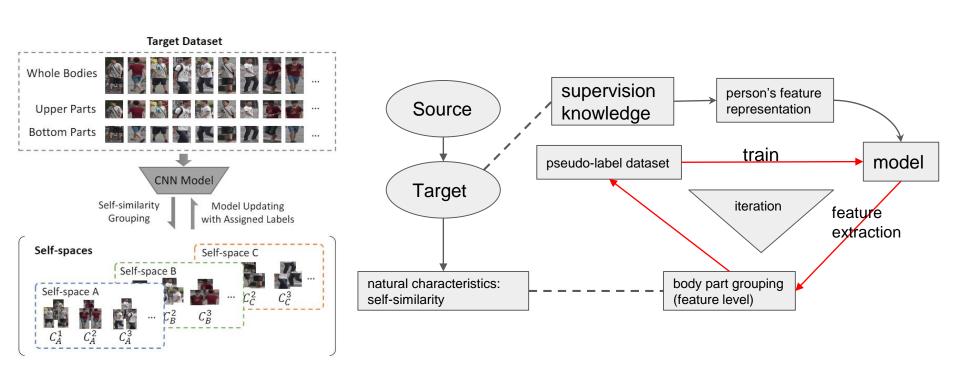
clustering-based

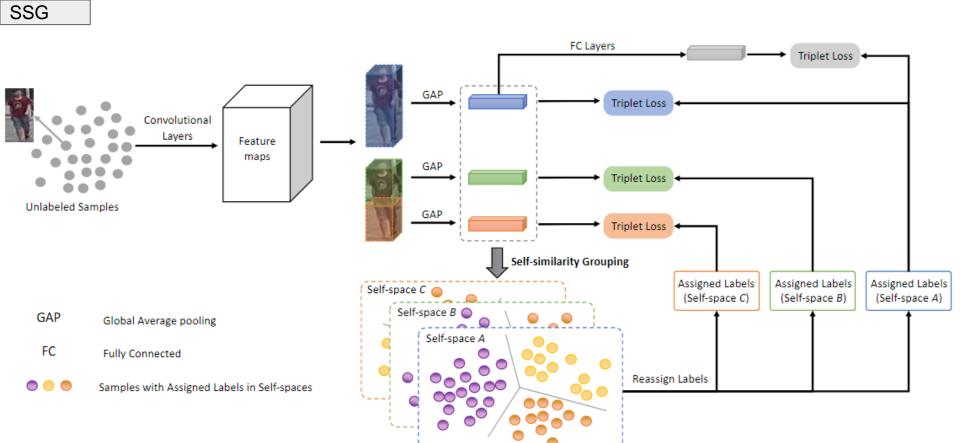
ECN[CVPR 19], PAUL[CVPR 19], SSG[ICCV 19], PAST[ICCV 19]

UDA Re-Identification: Theory and Practice(arxiv)

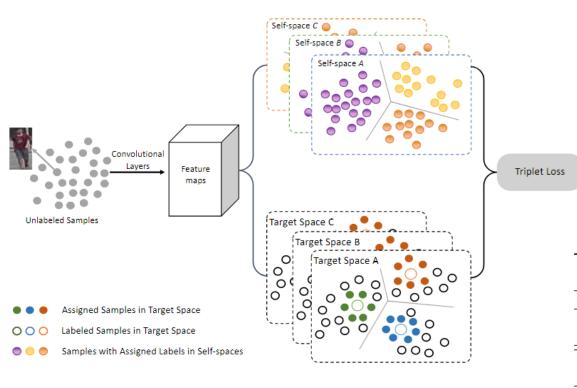


Self-similarity Grouping: A Simple Unsupervised Cross Domain Adaptation Approach for Person Re-identification (ICCV 2019)





step-wise learning approach: use pseudo-labeled dataset generated by clustering for training



Source	DukeMTMC-reID
Target	Market-1501

Methods	mAP	R1	R5	R10
SSG	58.3	80.0	90.0	92.4
SSG^{++}	68.7	86.2	94.6	96.5

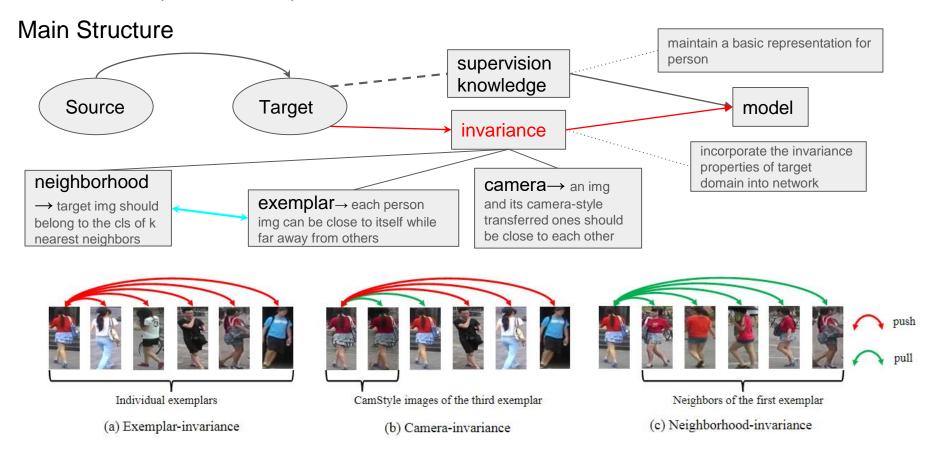
Source	Market-1501						
Target			DukeMTMC-reID				
Methods	mAl	•	R1	R5	R10		
SSG	53.4		73.0	80.6	83.2		
SSG^{++}	60.3	;	76.0	85.8	89.3		

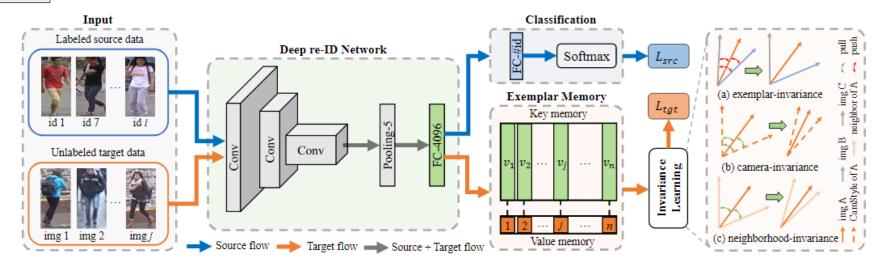
Methods	DukeMTMC-reID→ MSMT17					
	mAP	R1	R10			
PTGAN [40]	3.3	11.8	27.4			
SSG	13.3	32.2	51.2			
SSG ⁺⁺	18.3	41.6	62.2			

Methods	Market1501→ MSMT17					
Wiethous	mAP	R1	R10			
PTGAN [40]	2.9	10.2	24.4			
SSG	13.2	31.6	49.6			
SGG ⁺⁺	16.6	37.6	57.2			

ECN

Invariance Matters: Exemplar Memory for Domain Adaptative Person Reidentification (CVPR 2019)

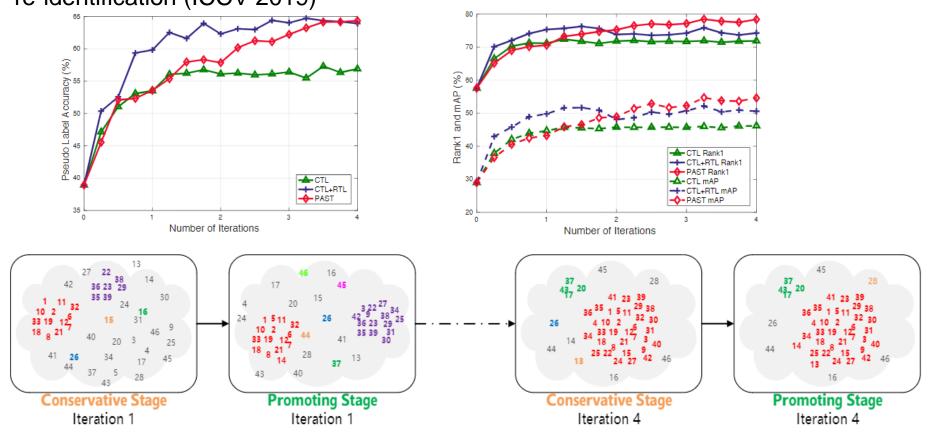




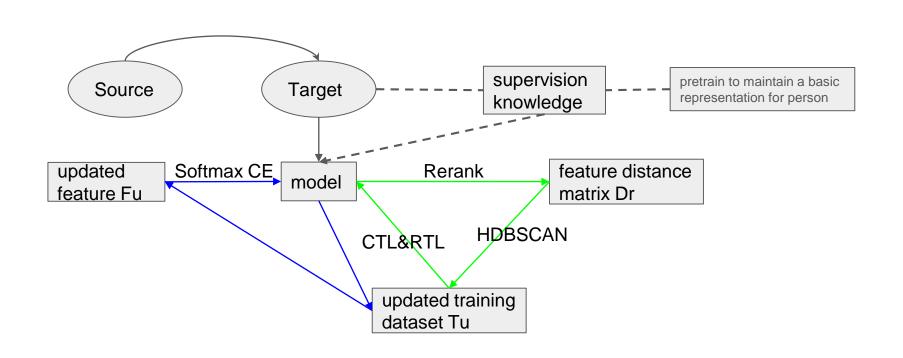
Methods		Marke	et-1501			DukeMTMC-reID			
Wethous	R-1	R-5	R-10	mAP	R-1	R-5	R-10	mAP	
LOMO [15]	27.2	41.6	49.1	8.0	12.3	21.3	26.6	4.8	
Bow [37]	35.8	52.4	60.3	14.8	17.1	28.8	34.9	8.3	
UMDL [20]	34.5	52.6	59.6	12.4	18.5	31.4	37.6	7.3	
PTGAN [30]	38.6	-	66.1	-	27.4	-	50.7	-	
PUL [9]	45.5	60.7	66.7	20.5	30.0	43.4	48.5	16.4	
SPGAN [7]	51.5	70.1	76.8	22.8	41.1	56.6	63.0	22.3	
CAMEL [36]	54.5	-	-	26.3	-	-	-	-	
MMFA [16]	56.7	75.0	81.8	27.4	45.3	59.8	66.3	24.7	
SPGAN+LMP [7]	57.7	75.8	82.4	26.7	46.4	62.3	68.0	26.2	
TJ-AIDL [29]	58.2	74.8	81.1	26.5	44.3	59.6	65.0	23.0	
CamStyle [45]	58.8	78.2	84.3	27.4	48.4	62.5	68.9	25.1	
HHL [43]	62.2	78.8	84.0	31.4	46.9	61.0	66.7	27.2	
Ours (ECN)	75.1	87.6	91.6	43.0	63.3	75.8	80.4	40.4	

Methods	Src.	MSMT17					
		R-1	R-5	R-10	mAP		
PTGAN [30]	Market	10.2	-	24.4	2.9		
Ours (ECN)	Market	25.3	36.3	42.1	8.5		
PTGAN [30]	Duke	11.8	-	27.4	3.3		
Ours (ECN)	Duke	30.2	41.5	46.8	10.2		

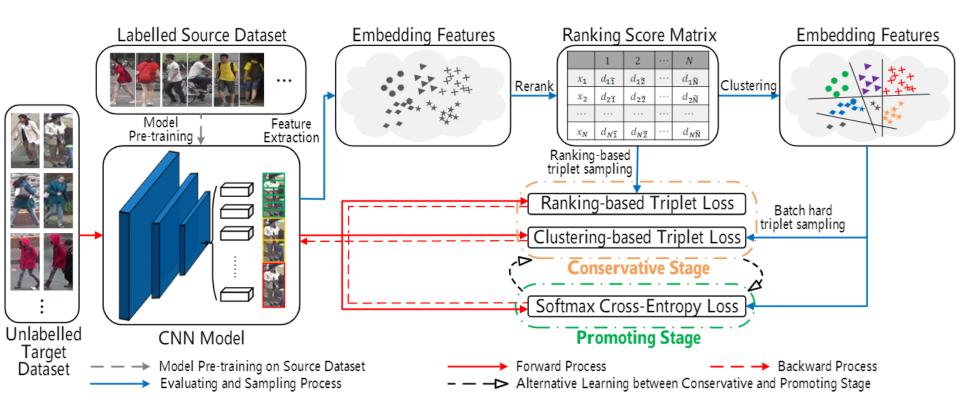
Self-training with progressive augmentation for unsupervised cross-domain person re-identification (ICCV 2019)



Main Structure



Progressive augmentation framework



Design of loss function

1. Clustering-based Triplet Loss(C-Stage)

$$L_{CTL} = \sum_{a=1}^{PK} [m + ||\mathbf{f}(x_a) - \mathbf{f}(x_p)||_2 - ||\mathbf{f}(x_a) - \mathbf{f}(x_n)||_2]_+ \qquad L_{RTL} = \sum_{a=1}^{PK} [\frac{|P_p - P_n|}{\eta}m + \sum_{\substack{hardest positive \\ p=1...K \\ j=1...K \\ j\neq i}} [m + \max_{\substack{p=1...K \\ j=1...P \\ j\neq i}} ||\mathbf{f}(x_{i,a}) - \mathbf{f}(x_{j,n})||_2]_+,$$

2. Ranking-based Triplet Loss(C-Stage)

$$L_{RTL} = \sum_{a=1}^{PK} \left[\frac{|P_p - P_n|}{\eta} m + ||\mathbf{f}(x_a) - \mathbf{f}(x_p)||_2 - ||\mathbf{f}(x_a) - \mathbf{f}(x_n)||_2 \right]_+$$

Total loss(C-Stage)

$$L_C = L_{RTL} + \lambda L_{CTL}$$

CE loss(P-Stage)

$$L_P = -\sum_{i=1}^{PK} \log \frac{e^{W_{\hat{y}_i}^T x_i}}{\sum_{c=1}^C e^{W_c^T x_i}}$$

Result of UDA

11000.110.								
Methods		D> Marl	ket-1501		M> DukeMTMC-re-ID			
ivietnods	R-1	R-5	R-10	mAP	R-1	R-5	R-10	mAP
LOMO(CVPR 2015)	27.2	41.6	49.1	8	12.3	21.3	26.6	4.8
UMDL(CVPR 2016)	34.5	52.6	59.6	12.4	18.5	31.4	37.6	7.3
Bow(ICCV 2015)	35.8	52.4	60.3	14.8	17.1	28.8	34.9	8.3
PTGAN(CVPR 2018)	38.6		66.1		27.4		50.7	
PUL(ACM TOMM 2018)	45.5	60.7	66.7	20.5	30	43.4	48.5	16.4
SPGAN(CVPR 2018)	51.5	70.1	76.8	22.8	41.1	56.6	63	22.3
CAMEL(ICCV 2017)	54.5			26.3				
ATNet(CVPR 2019)	55.7	73.2	79.4	25.6	45.1	59.5	64.2	24.9
MMFA(BMVC 2018)	56.7	75	81.8	27.4	45.3	59.8	66.3	24.7
SPGAN+LMP(CVPR 2018)	57.7	75.8	82.4	26.7	46.4	62.3	68	26.2
TJ-AIDL(CVPR 2018)	58.2	74.8	81.1	26.5	44.3	59.6	65	23
CamStyle(TIP 2019)	58.8	78.2	84.3	27.4	48.4	62.5	68.9	25.1
HHL(ECCV 2018)	62.2	78.8	84	31.4	46.9	61	66.7	27.2
BUC(AAAI 2019)	66.2	79.6	84.5	38.3	47.4	62.6	68.4	27.5
PAUL(CVPR 2019)	68.5	82.4	87.4	40.1	72	82.7	86	53.2
DBC(arxiv 2019)	69.2	83	87.8	41.3	51.5	64.6	70.1	30
E-cluster(arxiv 2019)	70.2		88.6	42.8	52.7		70.6	31.4
ECN(CVPR 2019)	75.1	87.6	91.6	43	63.3	75.8	80.4	40.4
theory&practice(arxiv 2018)	75.8	89.5	93.2	53.7	68.4	80.1	83.5	49
PAST(ICCV 2019)	78.38			54.62	72.35			54.26
SSG(ICCV 2019)	80	90	92.4	58.3	73	80.6	83.2	53.4
SSG++	86.2	94.6	96.5	68.7	76	85.8	89.3	60.3