Semi-supervised Person Re-identification by Attribute Similarity Guidance

Peixian Hong[1], Ancong Wu[1] and Wei-Shi Zheng[1,2,*]
[1]School of Data and Computer Science, Sun Yat-sen University, China
[2]Key Laboratory of Machine Intelligence and Advanced Computing, Ministry of Education, China
Email: hongpx@mail2.sysu.edu.cn, wuanc@mail.sysu.edu.cn, wszheng@ieee.org

Introduction

- **Goal**

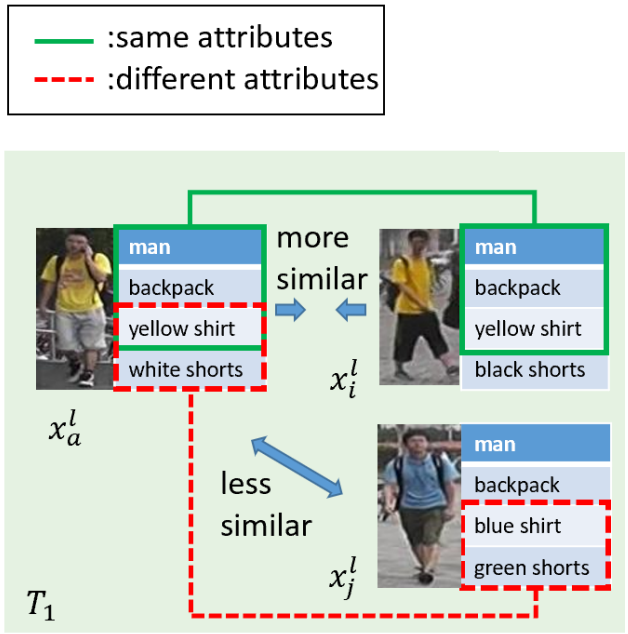
✓ Study the semi-supervised person re-identification (Re-ID)

✓ Exploit pedestrian attribute annotation as auxiliary information.

- **Advantages of attribute**

✓ Easily labeled

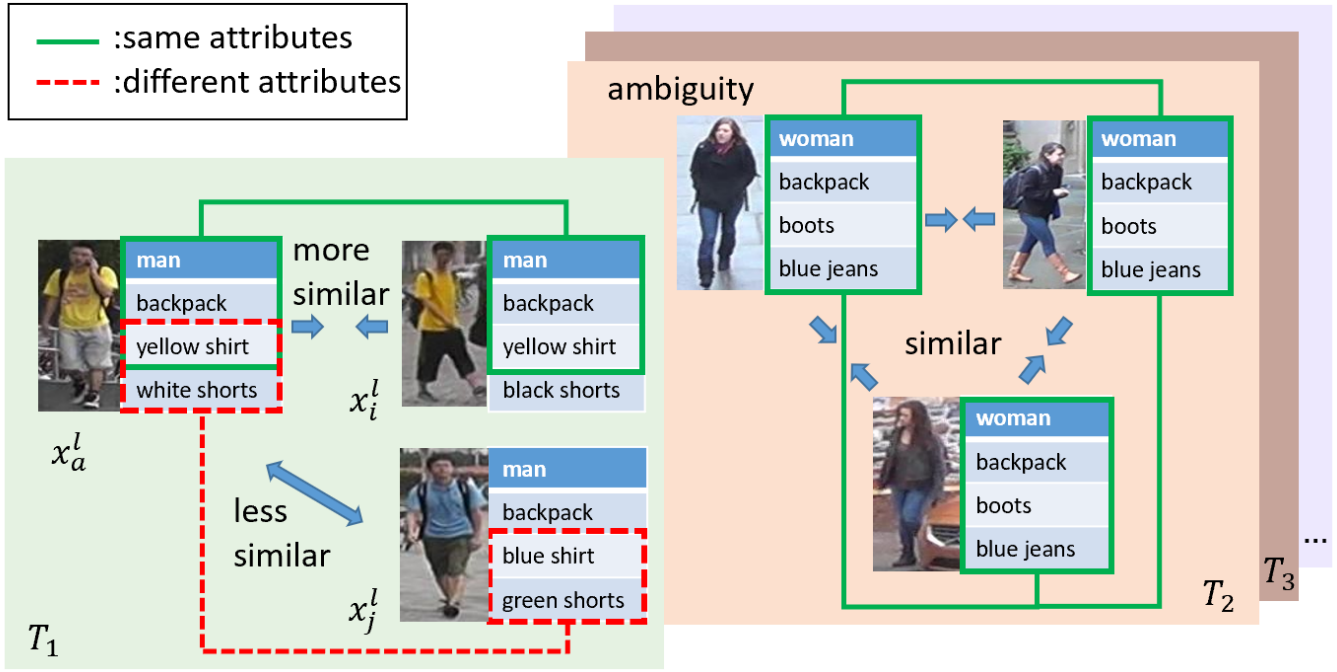
✓ Provide coarse semantic knowledge of the degree of similarity between different persons



Introduction

- **Challenge**

Ambiguity: different persons may have very similar attributes.

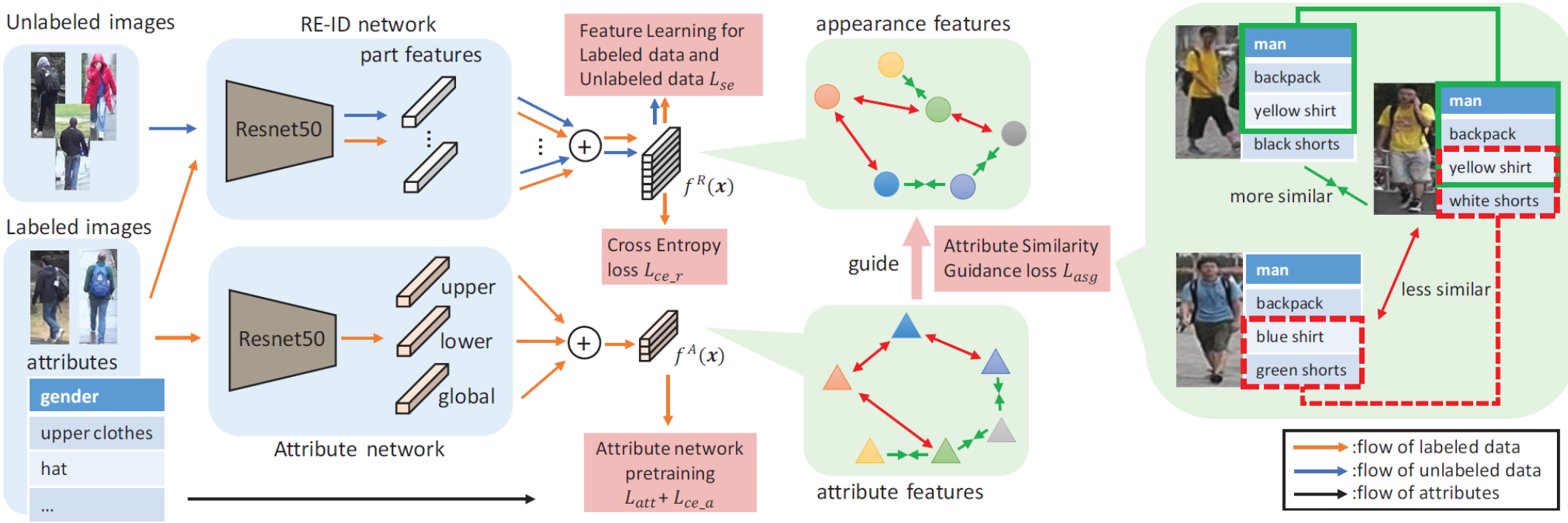


Introduction

- **Our method**

✓ An attribute Similarity Guidance loss (ASG) with the constraint of selective attribute similarity preservation

✓ An attribute-guided self training framework



Methodology

- **Attribute Network Pretraining**
- **Guiding RE-ID Network using Attribute Similarity**

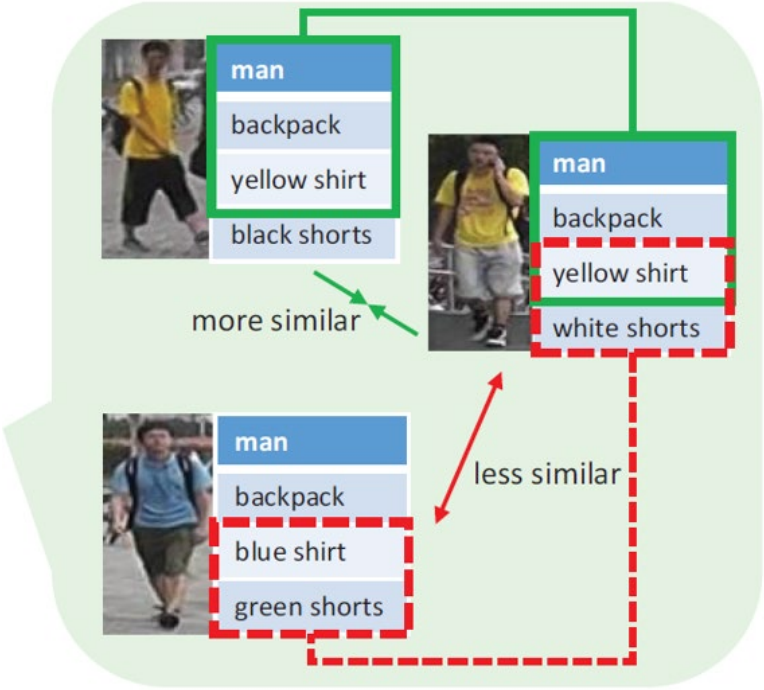
Attribute similarity guidance loss with the constraint of selective attribute similarity preservation

$$\min \left| s^R_{a,i}/s^R_{a,j} - s^A_{a,i}/s^A_{a,j} \right|$$

$$L_{asg} = \begin{cases} \sum_{(a,i,j)\in\mathbb{N}} \left| \frac{s^R_{a,i}}{s^R_{a,j}} - \frac{s^A_{a,i}}{s^A_{a,j}} \right|, & (s^R_{a,i} - s^R_{a,j})(s^A_{a,i} - s^A_{a,j}) < 0, \\ 0, & (s^R_{a,i} - s^R_{a,j})(s^A_{a,i} - s^A_{a,j}) \geq 0, \end{cases}$$

selective attribute similarity preservation

Attribute Similarity Guidance loss L_{asg}



Methodology

- **Attribute-Guided Self Training Framework**

✓ Memory-based feature learning

$$L^m = -\log \frac{\sum\limits_{\mathbf{v}_j^u \in K_i^u} e^{-s\|f^R(\mathbf{x}_i^u)-\mathbf{v}_j^u\|_2^2}}{\sum\limits_{j=1,j\neq i}^{n_u} e^{-s\|f^R(\mathbf{x}_i^u)-\mathbf{v}_j^u\|_2^2} + \sum\limits_{\mathbf{v}_j^l \in K_i^l} e^{-s\|f^R(\mathbf{x}_i^u)-\mathbf{v}_j^l\|_2^2}},$$

✓ Clustering-based feature learning.

$$\begin{aligned} L^c = &\left[\|f^R(\mathbf{x}_a^u) - f^R(\mathbf{x}_p^u)\|_2^2 - \|f^R(\mathbf{x}_a^u) - f^R(\mathbf{x}_n^u)\|_2^2 + m\right]_+ \\ &+ \left[\|f^R(\mathbf{x}_a^u) - f^R(\mathbf{x}_p^u)\|_2^2 - \|f^R(\mathbf{x}_a^u) - f^R(\mathbf{x}_n^l)\|_2^2 + m\right]_+ \end{aligned}$$

✓ Dynamic Weighted Optimizing.

$$L_{se} = \frac{1}{U}\sum_{i=1}^{U} L_i^m + \frac{1}{U}\sum_{a=1}^{U} L_a^c$$

$$L = aL_{guide} + (1-a)L_{se}$$

Results

- **Experiment setting**

randomly selected 40 identities as labeled data and the remaining identities served as unlabeled data

- **Comparison with related methods**

source dataset	Market-1501				
target dataset	DukeMTMC				
Methods	labeled IDs	R-1	R-5	R-10	mAP
LSRO [6]	40 IDs	27.1	40.3	47.0	9.0
All-in-one [27]	40 IDs	43.5	58.3	64.3	21.1
Pseudo label [22]	40 IDs	45.2	60.2	66.7	23.5
TCP [3]	40 IDs	65.8	78.2	82.5	44.4
EDS [5]	40 IDs	66.1	78.6	82.1	44.3
PAUL [12]	40 IDs	61.9	74.6	78.9	40.3
SSG [15]	40 IDs	73.8	83.0	86.7	54.3
Ours	40 IDs	75.2	84.0	87.2	55.9

source dataset	DukeMTMC				
target dataset	Market-1501				
Methods	labeled IDs	R-1	R-5	R-10	mAP
LSRO [6]	40 IDs	37.2	54.1	60.7	12.6
All-in-one [27]	40 IDs	52.4	69.6	75.6	21.3
Pseudo label [22]	40 IDs	54.1	71.7	78.1	24.4
TCP [3]	40 IDs	75.4	88.8	92.6	48.1
EDS [5]	40 IDs	72.4	87.2	90.7	45.0
PAUL [12]	40 IDs	69.7	82.9	87.7	41.2
SSG [15]	40 IDs	82.3	92.0	94.5	61.6
Ours	40 IDs	84.4	92.9	95.1	63.7

source dataset	-				
target dataset	DukeMTMC				
Methods	labeled IDs	R-1	R-5	R-10	mAP
LSRO [6]	40 IDs	22.9	35.7	42.3	8.8
All-in-one [27]	40 IDs	32.5	48.6	56.7	16.7
Pseudo label [22]	40 IDs	40.6	56.5	63.8	21.3
TCP [3]	40 IDs	51.9	67.4	72.3	31.1
EDS [5]	40 IDs	53.2	68.2	73.8	30.1
PAUL [12]	40 IDs	51.1	67.5	73.9	29.7
SSG [15]	40 IDs	65.6	78.0	81.6	46.0
Ours	40 IDs	71.9	81.4	84.7	51.5
MVC [4]	1/3 of all IDs	55.7	-	-	37.8
Ours	1/3 of all IDs	76.7	86.3	88.6	58.1

source dataset	-				
target dataset	Market-1501				
Methods	labeled IDs	R-1	R-5	R-10	mAP
LSRO [6]	40 IDs	33.2	51.6	60.4	11.5
All-in-one [27]	40 IDs	44.4	66.0	73.9	19.2
Pseudo label [22]	40 IDs	46.7	67.2	75.2	21.7
TCP [3]	40 IDs	60.7	77.2	83.1	32.1
EDS [5]	40 IDs	50.3	68.0	75.8	24.2
PAUL [12]	40 IDs	51.9	68.3	75.0	24.4
SSG [15]	40 IDs	70.9	85.0	89.8	46.2
Ours	40 IDs	78.1	89.1	92.0	52.7
MVC [4]	1/3 of all IDs	75.3	-	-	52.6
Ours	1/3 of all IDs	87.0	94.1	96.2	66.6

Results

- Ablation study

source dataset	-		-	
target dataset	Market-1501		DukeMTMC	
method	R-1	mAP	R-1	mAP
attribute net	50.5	26.8	44.0	23.0
reid net	60.4	34.3	51.2	30.2
reid net + ASG	65.3	37.3	57.6	36.3
reid net + ASG (w/o ASP)	57.0	30.6	48.3	27.4
reid net + ASG + SE	78.1	52.7	71.9	51.5

source dataset	DukeMTMC		Market-1501	
target dataset	Market-1501		DukeMTMC	
method	R-1	mAP	R-1	mAP
attribute net	62.4	34.9	57.9	36.8
reid net	71.7	44.2	63.8	42.4
reid net + ASG	73.6	45.3	65.8	44.5
reid net + ASG (w/o ASP)	72.0	43.6	64.0	42.8
reid net + ASG + SE	84.4	63.7	75.2	55.9

- Analysis on the number of known identities

source dataset	DukeMTMC		Market-1501	
target dataset	Market-1501		DukeMTMC	
known identities	R-1	mAP	R-1	mAP
20	82.8	59.4	72.3	53.9
40	84.4	63.7	75.2	55.9
80	85.5	65.5	76.1	56.2
fully supervised	93.3	78.3	83.9	70.3