Center based Pseudo-labeling for Semi-supervised Person Re-identification

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Motivation

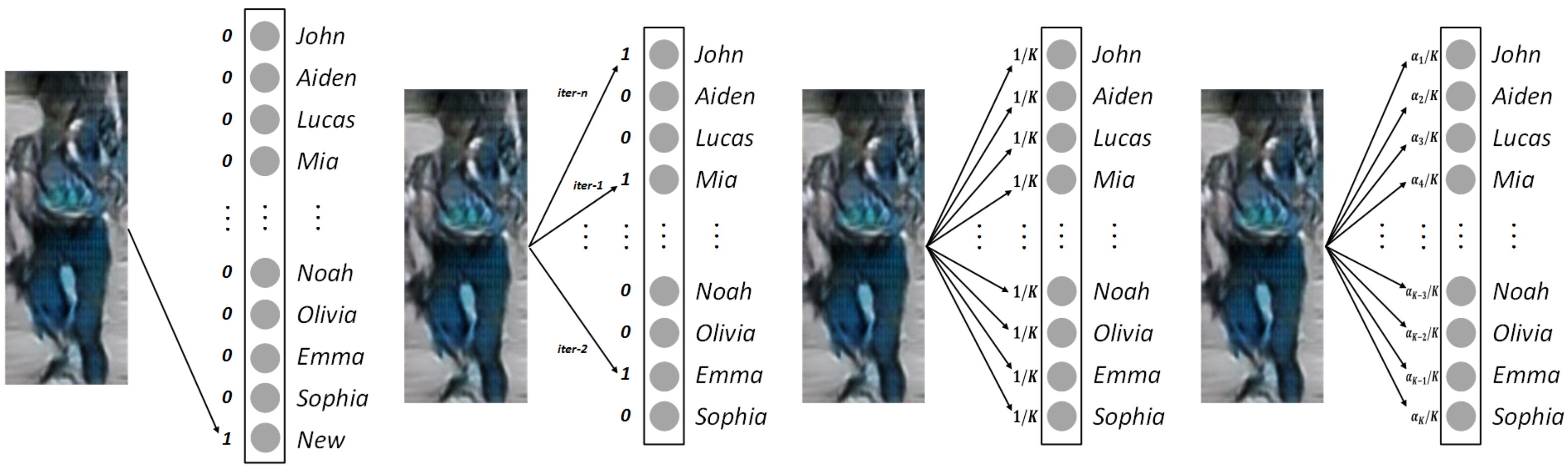
- Deep networks are data-hungry
- Considers both intra-class and inter-class variations
- Reason between labeled and unlabeled data

Contributions

- We introduce a multi-task loss function
- We propose a novel clustering based pseudo-labeling approach

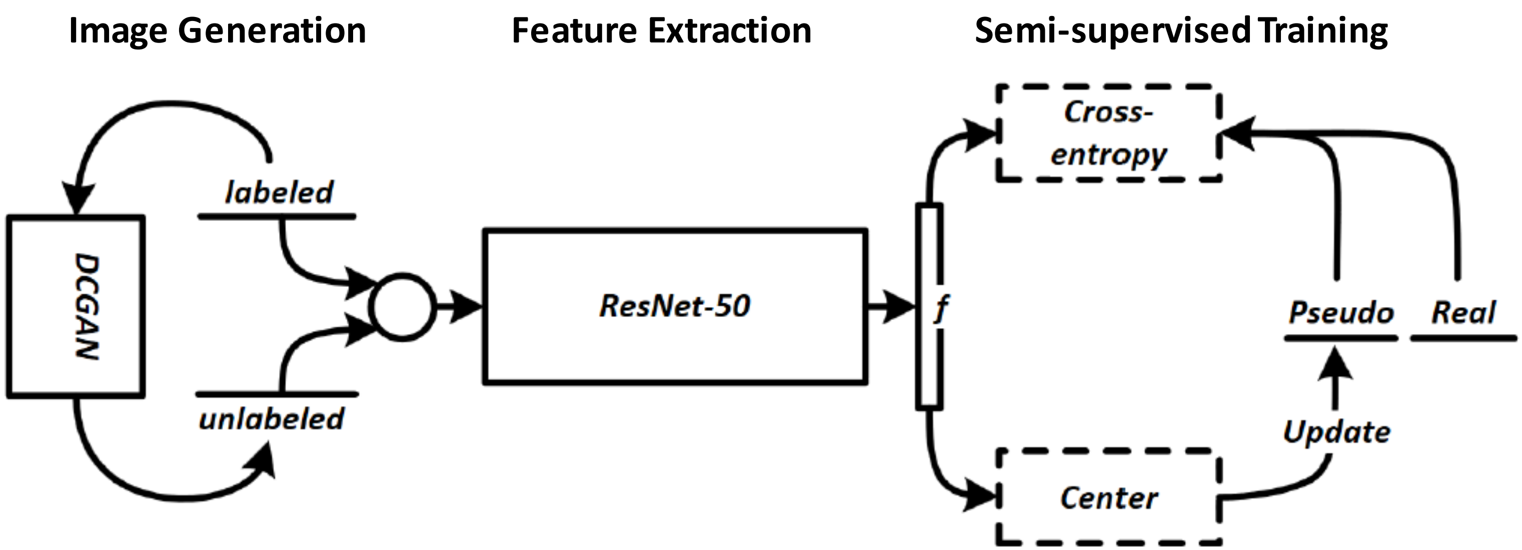
Method

- Pseudo-labels recap



Method

- Overall Architecture:



Method

Formulations:

- Multi-task loss

$$
\begin{aligned}
L &= L_S + \lambda L_C \\
&= -\sum_{i=1}^{m} \log \frac{e^{W_{y_i}^T x_i + b_{y_i}}}{\sum_{k=1}^{K} e^{W_{y_k}^T x_i + b_{y_k}}} + \frac{\lambda}{2} \sum_{i=1}^{m} \|x_i - c_{y_i}\|_2^2
\end{aligned}
$$

- Pseudo-labeling

$$
Y(u_i) = \arg\max_k sim(u_i, c_k), \quad s.t., k \in [1, K].
$$

where:

$$
sim(u_i, c_k) = \frac{u_i \cdot c_k}{\|u_i\| \|c_k\|}
$$

Method

- Derivatives/Update rules

$$\begin{aligned}\frac{\partial L}{\partial x_i} &= \frac{\partial L_S}{\partial x_i} + \frac{\lambda}{2}\frac{\partial L_C}{\partial x_i} \\ &= \frac{W_{y_i} \cdot e^{W_{y_i}^T x_i + b_{y_i}}}{\sum_{k=1}^{K} e^{W_{y_k}^T x_i + b_{y_k}}} - W_{y_i} + \lambda(x_i - c_{y_i})\end{aligned}$$

$$\Delta c_j = \frac{\sum_{i=1}^{m} \delta(x_i \in L) \cdot \delta(y_i = k) \cdot (c_k - x_i)}{1 + \sum_{i=1}^{m} \delta(x_i \in L) \cdot \delta(y_i = k)}$$

Experiments

Image Generation

- Network

DCGAN[1]

- Results

Real

Generated

[1] Radford A, Metz L, Chintala S. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks[J]. Computer Science, 2015.

Experiments

- Effectiveness of proposed approach

Table 1. Rank-1 accuracy (%) and mAP (%) on the Market-1501 dataset with varying numbers of unlabeled training data. Best results amongst approaches are in bold whilst best results for different unlabeled data incorporated is underlined.

#GAN images	All-in-one [9, 10]		One-hot Pseudo [11]		LSRO [2]		dMpRL-I [3]		dMpRL-II [3]		CPL(Ours)	
	rank-1	mAP	rank-1	mAP	rank-1	mAP	rank-1	mAP	rank-1	mAP	rank-1	mAP
0(baseline)	72.74	50.99	72.74	50.99	72.74	50.99	72.74	50.99	72.74	50.99	72.74	50.99
12000	76.96	55.68	76.52	55.69	77.17	55.22	77.88	55.84	79.22	58.14	**81.38**	**60.31**
18000	77.40	55.59	77.95	55.04	76.96	55.28	78.36	56.21	79.81	58.31	**82.10**	**62.31**
24000	77.21	56.07	77.62	56.90	78.21	56.33	77.79	56.10	80.37	58.59	**82.04**	**61.26**
30000	77.17	56.19	77.95	56.54	77.46	55.40	78.65	57.15	79.16	57.69	**82.10**	**61.42**
36000	75.92	55.24	77.42	56.38	77.91	55.82	78.95	57.42	79.90	57.61	**82.12**	**60.70**
improvement	4.66	5.20	5.21	5.91	5.47	5.34	6.21	6.43	7.63	7.60	**9.38**	**11.32**

Experiments

More Comparison

Table 2. Comparison of related approaches for pseudo-labeling on the DukeMTMC-reID dataset. Rank-1 accuracy (%) and mAP (%) are reported.

Method	rank-1	mAP
baseline	65.22	44.99
LSRO [2]	67.68	47.13
dMpRL [3]	68.24	48.58
CPL (Ours)	**70.92**	**51.99**

Table 3. Comparison with state-of-the-art methods on the Market-1501 dataset. Best and second best results are denoted in bold and underlined, respectively.

Method	Market 1501	
	rank-1	mAP
Gate-reID (ECCV'16) [14]	65.88	39.55
SCSP (CVPR'16) [15]	51.90	26.35
DNS (CVPR'16) [16]	61.02	35.68
ResNet+OIM (CVPR'17) [17]	82.10	-
Latent Parts (CVPR'17) [18]	80.31	57.53
P2S (CVPR'17) [19]	70.72	44.27
Consistent-Aware (CVPR'17) [20]	80.90	55.60
Spindle (CVPR'17) [21]	76.90	-
SSM (CVPR'17) [22]	82.21	<u>68.80</u>
JLML (IJCAI'17) [23]	**85.10**	65.50
SVDNet (ICCV'17) [24]	82.30	62.10
Part Aligned (ICCV'17) [25]	81.00	63.40
PDC (ICCV'17) [26]	84.14	63.41
LSRO (ICCV'17) [2]	78.06	56.23
dMpRL-II (Arxiv'18) [3]	80.37	58.59
Baseline	72.74	50.99
Ours	82.10	62.31
Ours+re-rank	<u>84.47</u>	**75.90**

Ablation study

Table 4. Ablative experiments about effectiveness of center regularization term and pseudo-labeling on Market-1501.

methods	rank-1	mAP	supervision
baseline	72.74	50.99	full
center	79.45	57.25	full
center + pseudo	82.10	62.31	semi

Conclusion

- CPL can reduce intra-class variations
- CPL generates labels based on feature similarity
- This method can improve the accuracy of person re-identification

Follow-up work

- Generalize the one-hot scheme of pseudo-labels to the distributed scheme
- Add extensive experiments and elaborations

Feature Affinity based Pseudo-Labeling for Person Re-identification
https://arxiv.org/abs/1805.06118.

Thanks!

Questions?

Any further inquires, contact me at
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