Domain Adaptation for Person Re-identification on New Unlabeled Data

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Schedule

Overview

The purpose of person re-identification is to match images of persons in non-overlapping cameras views.

In person re-identification, each dataset or network of cameras is a domain.

Figure 1: Example from Market 1501 [1] dataset

[1] Zheng, L., Shen, L., Tian, L., Wang, S., Wang, J., and Tian, Q. Scalable person re-identification: A benchmark. In: ICCV 2015.

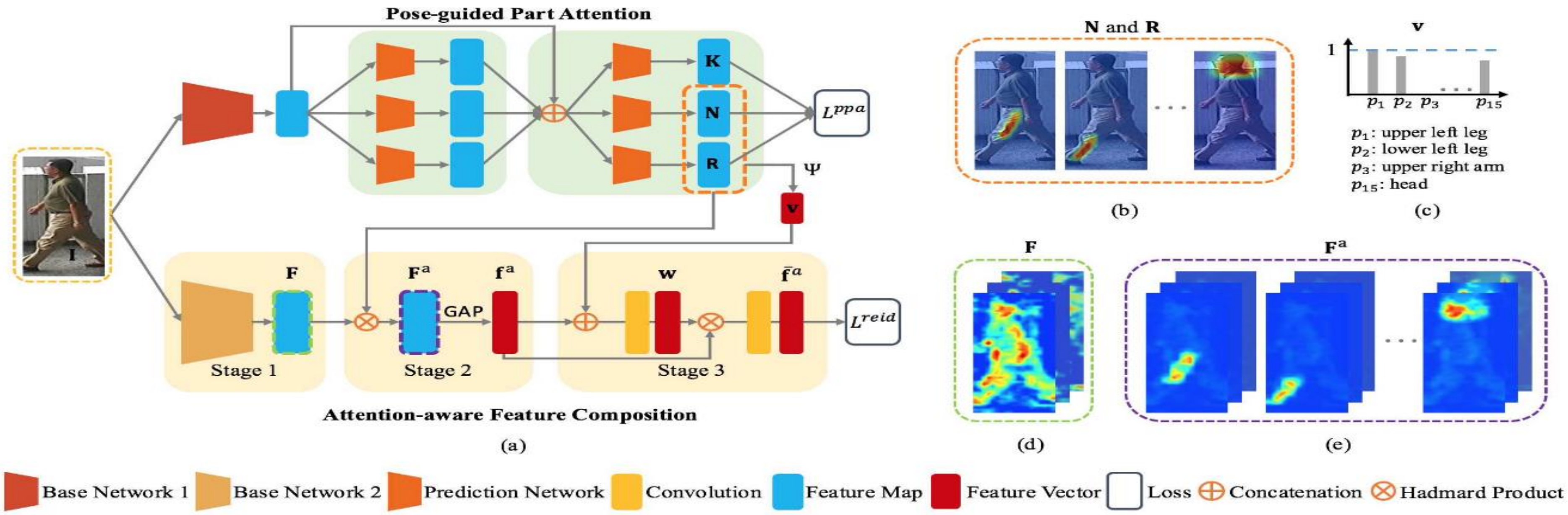
Objective

Our objective is to improve person re-identification performance on new datasets without the need of labeling it.

Related Work

The state-of-art on person re-identification uses either:

- **Attention-based neural networks [2]**
- **Factorization neural networks [3]**
- **Body parts detection [4]**



[2] Liu, X., Zhao, H., Tian, M., Sheng, L., Shao, J., Yi, S., Yan, J. and Wang, X. Hydraplus-net: Attentive deep features for pedestrian analysis. In: ICCV 2017.
[3] Chang, X., Hospedales, T. M., and Xiang, T. Multilevel factorization net for person re-identification. In: CVPR 2018.
[4] Zhao, H., Tian, M., Sun, S., Shao, J., Yan, J., Yi, S., Wang, X., and Tang, X. Spindle net: Person reidentification with human body region guided feature decomposition and fusion. In: CVPR 2017.

Related Work

The person re-identification challenge can be approached as:

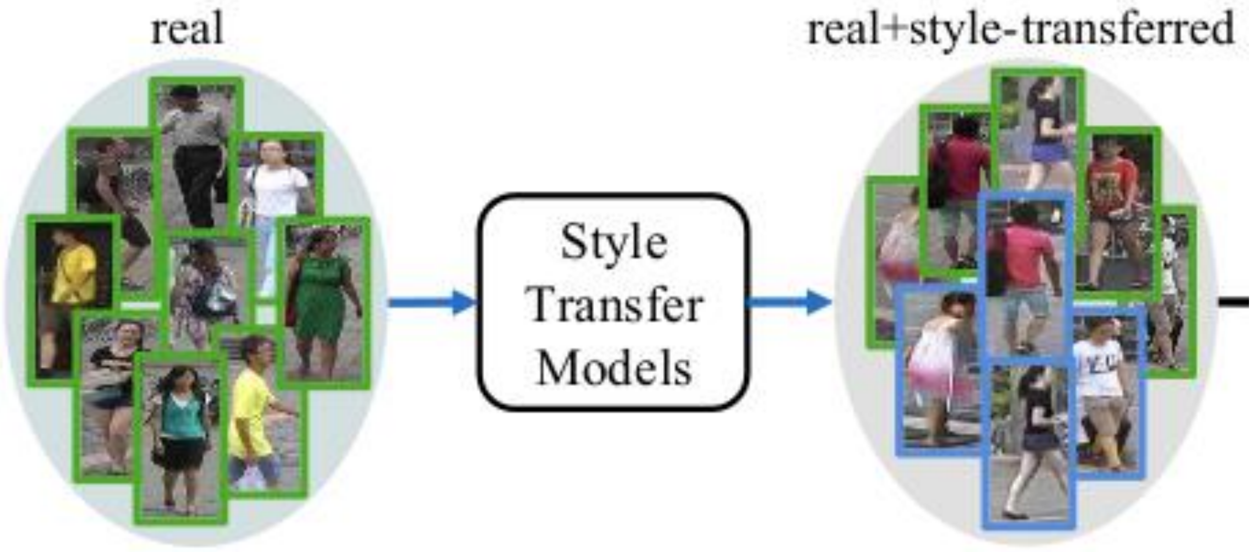
- **metric learning task [4][5]**
- **classification task [2][3]**

[5] Deng, W., Zheng, L., Ye, Q., Kang, G., Yang, Y., and Jiao, J. Image-image domain adaptation with preserved self-similarity and domain-dissimilarity for person re-identification. In: CVPR 2018.

Related Work

Domain adaptation techniques for person re-identification:

- **Direct transfer [4]**
- **Camera style adaptation [6]**
- **Domain guided dropout [7]**



[6] Zhong, Z., Zheng, L., Zheng, Z., Li, S., and Yang, Y. Camera style adaptation for person reidentification. In: CVPR 2018.
[7] Xiao, T., Li, H., Ouyang, W., and Wang, X. Learning deep feature representations with domain guided dropout for person re-identification. In: CVPR 2016.

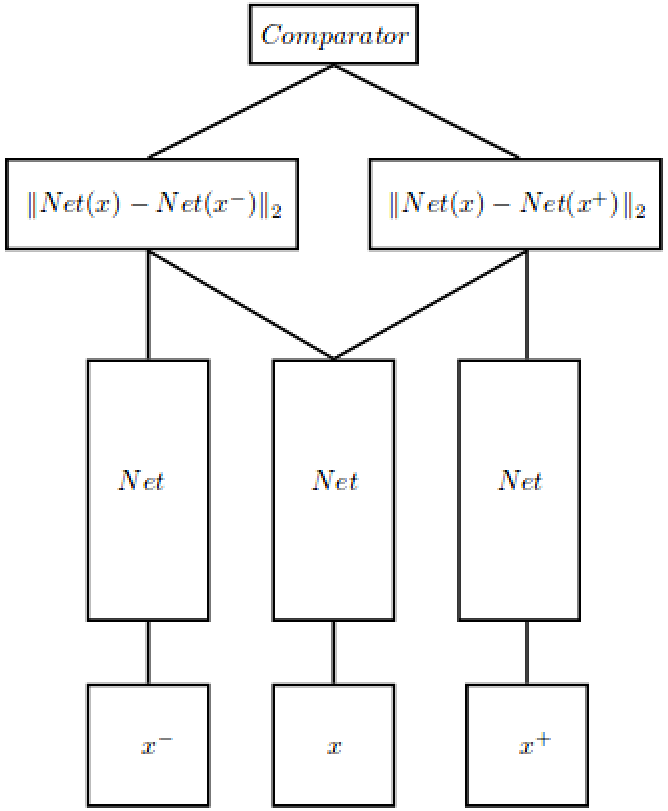
Proposed Method – Direct Transfer [4]

Our baseline method had the following configurations:

- **ResNet-50**
- **Pre-trained on ImageNet**
- **Triplet loss with batch hard [8]**
- **Adam optimizer**
- **Batch scheduler**

Algorithm 1 Batch Scheduler

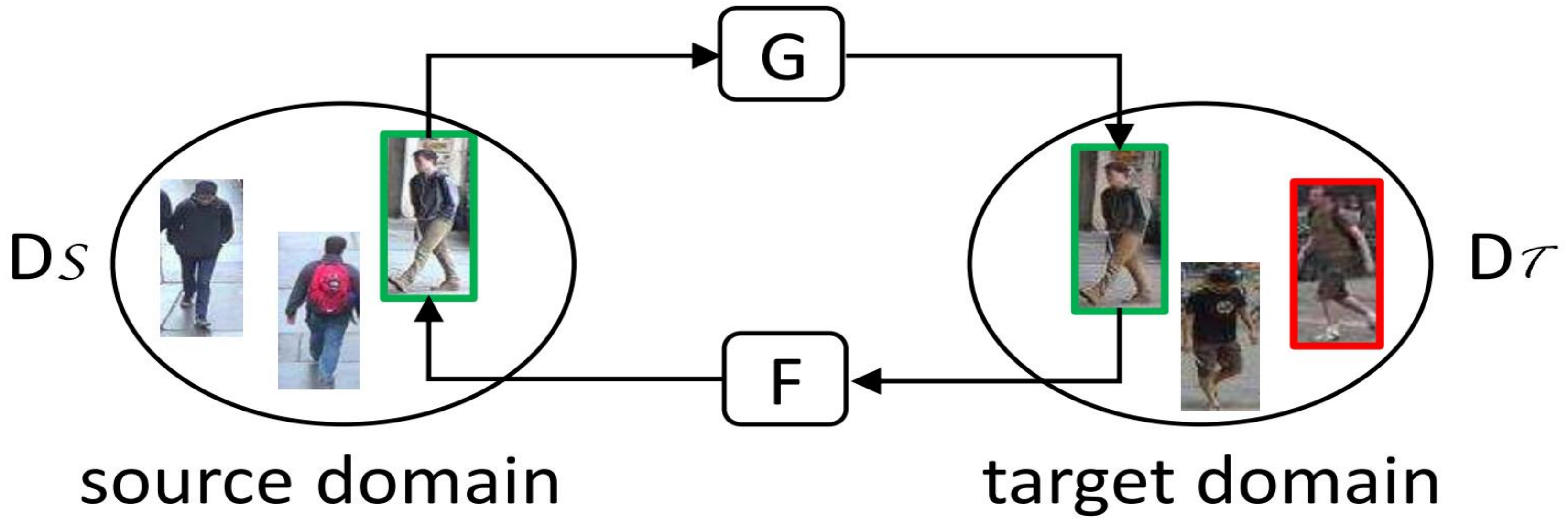
$batch\_size = 8$
$m = 0.5$ // m is the loss margin of Eq. 1
for $i = 0$ to num_epochs **do**
  $loss = train(i, batch\_size)$
  if $loss < 0.8 \times m$ **then**
    $batch\_size = batch\_size + 8$
  end if
end for



[8] Hermans, A., Beyer, L., and Leibe, B. In defense of the triplet loss for person re-identification. arXiv 2017.

Proposed Method – CycleGAN [5]

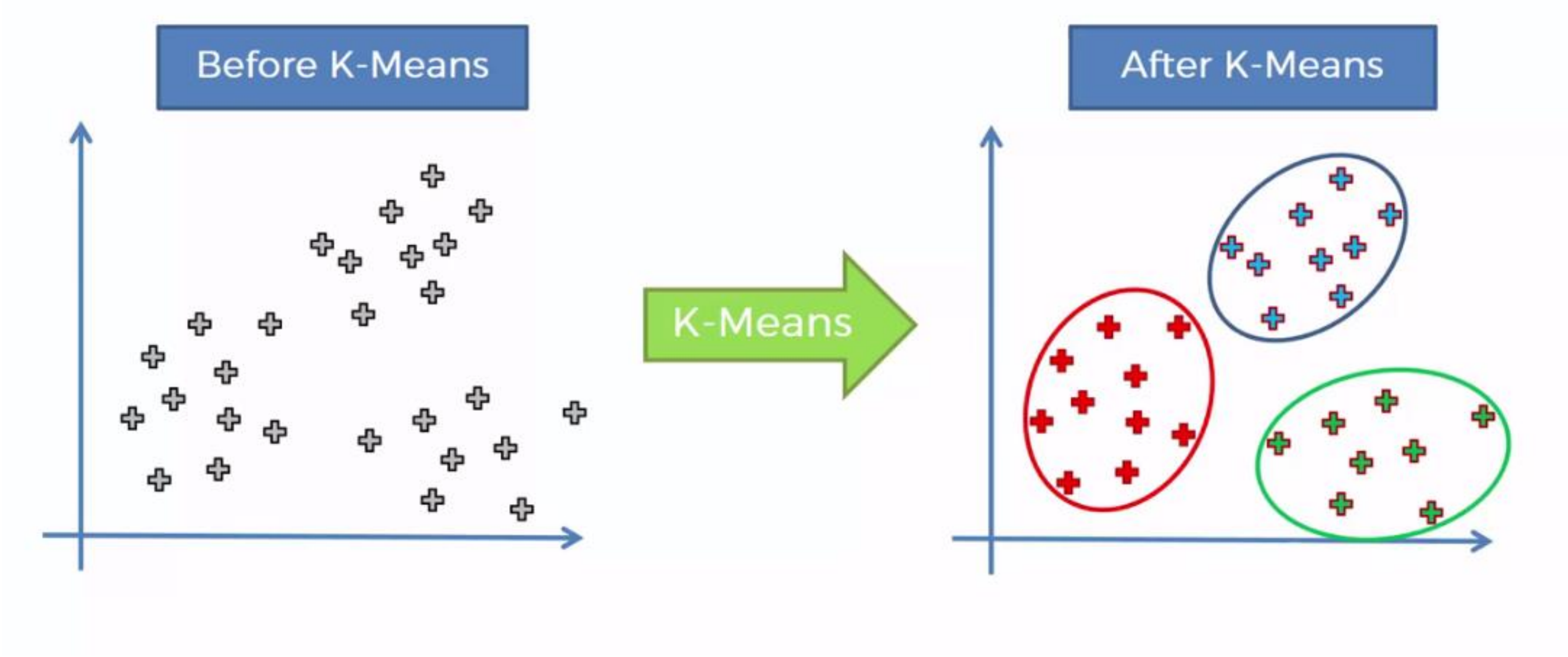
Train CycleGAN [9] with images from source and target domain → Generate Intermediate Dataset → Fine Tune the CNN using the intermediate dataset



[5] Deng, W., Zheng, L., Ye, Q., Kang, G., Yang, Y., and Jiao, J. Image-image domain adaptation with preserved self-similarity and domain-dissimilarity for person re-identification. In: CVPR 2018.
[9] Zhu, J.-Y., Park, T., Isola, P., and Efros, A. A. Unpaired image-to-image translation using cycle consistent adversarial networks. In: ICCV 2017.

Proposed Method – Pseudo label

Extract Features from target domain images → Group these features using k-means [10] → Generate a pseudo labelled dataset with the grouped features → Fine Tune the CNN using the pseudo labelled dataset



[10] Hartigan, J. A. and Wong, M. A. A K-means clustering algorithm. In: Journal of the Royal Statistical Society 1979.

Experimental Results - CycleGAN

Experimental Results - CycleGAN

			Accuracy (CMC scores)		
Target Domain	**Source Domain**	**Method**	**Rank – 1**	**Rank - 5**	**Rank - 10**
Market 1501	**Viper**	Direct Transfer	5.7%	15.5%	22.2%
		CycleGAN	**6.7%**	**17.0%**	**23.7%**
	CUHK 03	Direct Transfer	26.8%	45.9%	55.1%
		CycleGAN	**35.8%**	**56.5%**	**65.7%**
CUHK 03	**Viper**	Direct Transfer	5.9%	18.1%	29.0%
		CycleGAN	**31.9%**	**64.4%**	**77.5%**
	Market 1501	Direct Transfer	19.9%	49.4%	63.2%
		CycleGAN	**34.8%**	**66.7%**	**79.1%**
Viper	**CUHK 03**	Direct Transfer	10.1%	22.5%	29.0%
		CycleGAN	**11.6%**	**25.5%**	**34.7%**
	Market 1501	Direct Transfer	**12.5%**	25.0%	33.1%
		CycleGAN	9.8%	**26.9%**	**36.4%**

Experimental Results - Pseudo labels

Experimental Results - Pseudo labels

			Accuracy (CMC scores)		
Target Domain	**Source Domain**	**Method**	**Rank – 1**	**Rank - 5**	**Rank - 10**
Market 1501	**Viper**	Direct Transfer	5.7%	15.5%	22.2%
		CycleGAN	6.7%	17.0%	23.7%
		Ours	**8.6%**	**20.5%**	**28.4%**
	CUHK 03	Direct Transfer	26.8%	45.9%	55.1%
		CycleGAN	35.8%	56.5%	65.7%
		Ours	**37.3%**	**60.4%**	**70.4%**
CUHK 03	**Viper**	Direct Transfer	5.9%	18.1%	29.0%
		CycleGAN	31.9%	64.4%	77.5%
		Ours	**36.1%**	**69.2%**	**81.3%**
	Market 1501	Direct Transfer	19.9%	49.4%	63.2%
		CycleGAN	34.8%	66.7%	79.1%
		Ours	**38.2%**	**69.7%**	**81.6%**
Viper	**CUHK 03**	Direct Transfer	10.1%	22.5%	29.0%
		CycleGAN	11.6%	25.5%	34.7%
		Ours	**13.6%**	**33.9%**	**46.0%**
	Market 1501	Direct Transfer	12.5%	25.0%	33.1%
		CycleGAN	9.8%	26.9%	36.4%
		Ours	**13.9%**	**29.0%**	**40.7%**

Conclusions and Future Works

Conclusions:

1. Pseudo-labels lead to a significant boost in the performance
2. Batch scheduler plays a crucial role in triplet loss training in noisy datasets
3. The presented domain adaptation workflow is a great jump start for the deployment of person re-ID software in real applications

Future works:

1. Re-apply the pseudo-labels method in an iterative manner
2. Experiment other clustering algorithms to generate pseudo-labels

Thank You!