Unsupervised Domain Adaptation for Person Re-Identification through Source-Guided Pseudo-Labeling

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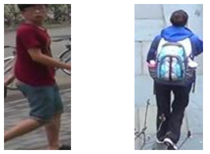
Context and problem

- Supervised learning for Person Re-identification (re-ID):

➔ **Poor generalization ability** to data from new context (domain)
➔ **Needs lot of labeled samples**



Train on \Test on (mAP %)	Market -1501	DukeMTMC-ReID
Market-1501	78.2	11.9
DukeMTMC-ReID	19.1	65.4

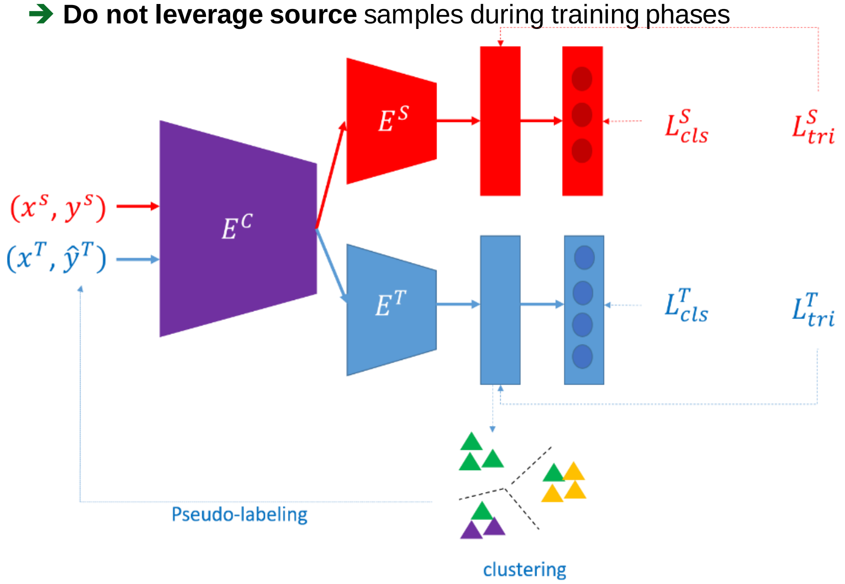
- How to transfer the performance of a re-ID model to a domain of interest (target domain) **without additional annotation** ?

- **Unsupervised Domain Adaptation (UDA):**

➔ Labeled samples from source domain S
➔ Unlabeled samples from target domain T
➔ Best performance on target

- **Pseudo-label methods**:

➔ Most efficient approach in re-ID UDA
➔ **Overfit** errors in pseudo-labels
➔ **Do not leverage source** samples during training phases



Our approach

- Our **Source-Guided (SG)** pseudo-label framework leverages the labeled source training set to **reduce pseudo-label noise overfitting.**

- **Source-Guidance** simply relies on:

➔ **Source re-ID feature learning** (ID Classification Loss L_{cls} and Triplet Loss L_{tri}): reduce pseudo-label noise overfitting

➔ **Domain-Specific batch normalization:** to cope domain discrepancy that degrades learning with batch norm

➔ **Domain-Specific two-branches architecture:** avoid biasing the target features with source domain

Experiments

- Source-Guided **(+SG)** pseudo-labeling improves performances over target-only pseudo-labeling on several UDA benchmarks

- SG **can easily be plugged in** various existing pseudo-labeling frameworks like MMT [1]

- SG improves pseudo-labeling especially when:

➔ No additional pseudo-label error robustness strategy
➔ Hard adaptation tasks (MSMT target)

- SOTA comparison:

➔ Competitive results on Market to Duke and Duke to Market
➔ **+ 0,6% mAP on Market to MSMT and +4% on Duke to MSMT**

COMPARISON WITH STATE-OF-THE-ART METHODS.

Methods	Market-to-Duke		Duke-to-Market	
	mAP	top-1	mAP	top-1
SPGAN [2]	22.3	41.1	22.8	51.5
TJ-AIDL [16]	23.0	44.3	26.5	58.2
MMFA [9]	24.7	45.3	38.3	66.2
HHL [23]	27.2	46.9	31.4	62.2
CFSM [1]	27.3	49.8	28.3	61.2
UCDA-CCE [12]	31.0	47.7	30.9	60.4
ARN [7]	33.4	60.2	39.4	70.3
ECN [24]	40.4	63.3	43.0	75.1
PoseDA-Net [8]	45.1	63.2	47.6	75.2
UDAP [14]	49.0	68.4	53.7	75.8
SSG [3]	53.4	73.0	58.3	80.0
ISSDA-re-ID [15]	54.1	72.8	63.1	81.3
PCB-PAST [21]	54.3	72.4	54.6	78.4
ACT [18]	54.5	72.4	60.6	80.5
MMT [4]	**65.1**	78.0	**71.2**	87.7
(target-only) baseline	50.1	70.1	54.3	73.5
baseline+SG	55.6	73.2	59.1	80.8
baseline+MMT+SG	64.8	**78.5**	70.5	**88.1**

Methods	Market-to-MSMT		Duke-to-MSMT	
	mAP	top-1	mAP	top-1
PTGAN [17]	2.9	10.2	3.3	11.8
ECN [12]	8.5	25.3	10.2	30.2
UDAP [14]	12.0	30.5	16.0	39.2
SSG [3]	13.2	49.6	13.3	32.2
MMT [4]	22.9	49.2	23.5	50.1
(target-only) baseline	11.6	29.8	14.8	36.1
baseline+SG	14.9	35.4	19.3	45.6
baseline+MMT+SG	**23.5**	**50.2**	**27.5**	**56.1**

References

[1] Ge, Yixiao, Dapeng Chen, and Hongsheng Li. "Mutual mean-teaching: Pseudo label refinery for unsupervised domain adaptation on person re-identification." arXiv preprint arXiv:2001.01526 (2020).