Take More Positives: A Contrastive Learning Framework for Unsupervised Person Re-Identification

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Abstract

Exploring the relationship between examples without manual annotations is a core problem in the field of unsupervised person re-identification (re-ID). In the unsupervised scenario, no ground truth is provided for bringing instances of the same identity closer and spreading samples of different identities apart. In this paper, we introduce a contrastive learning framework for unsupervised person re-ID, which we call Take More Positives (TMP). In an iterative manner, TMP generates pseudo-labels by clustering samples, and updates itself with such pseudo-labels and the proposed contrastive loss. By considering more positive examples, the framework of TMP outperforms the state-of-the-art methods for unsupervised person re-ID. On the Market-1501 benchmark, TMP achieves 88.3\% Rank-1 accuracy and 70.4\% mean average precision. Our code will be made publicly available.

1. Introduction

Unsupervised person re-identification (re-ID) aims at learning discriminative representations for person identities from unlabeled person images. In common person re-ID settings, manual annotations are provided as supervisory signals to reduce the distance between instances of the same person (positive pairs), and increase the distance between instances of different persons (negative pairs). Since instances of the same identity vary significantly under different camera views, it is challenging to model intra-class variations without ground truths in person re-ID. In other words, exploring the relationship between unlabeled person images is a core problem of unsupervised person re-ID.

In this paper, we introduce Take More Positives (TMP), a contrastive learning framework for unsupervised person re-ID. Before each training epoch, TMP first generates pseudo-labels by clustering samples. In an iterative manner, TMP is updated by pseudo-labels and the proposed contrastive loss. Intuitively, pseudo-label generation by clustering should be proceeded carefully as noisy pseudo-labels may mislead the training process and have a negative impact on the performance [17, 32]. However, our empirical results indicate that a loose clustering instead leads to good performance in unsupervised person re-ID, as opposed to our intuition.

In addition to the loose clustering and the more positive pairs derived from it, we propose a novel contrastive learning loss for training. Inspired by [10, 2], our contrastive loss brings features of instances with the same class closer on the unit hypersphere, and forces data points of different classes away from each other (see the feature distribution learned by our framework in Figure 1). Compared to
contrastive learning methods that only use one positive pair for each data point [2], we consider more positive examples with noisy pseudo-labels and achieve state-of-the-art results in unsupervised person re-ID.

To better understand what makes our contrastive learning loss work well with noisy pseudo-labels, we study the major components of our framework and show that:

- Similar to self-supervised representation learning, data augmentation operations and the idea of using differently augmented views of an image as a positive pair are crucial in unsupervised person re-ID.
- A loose clustering makes our framework take into account more positive in addition to many negatives, resulting in good person re-ID performance. Moreover, too many false negatives at the start of training overwhelm models.

Based on these findings, our framework TMP outperforms the state-of-the-art methods in unsupervised person re-ID. On the Market-1501 benchmark, TMP achieves 88.3% Rank-1 accuracy and 70.4% mean average precision, outperforming previous state-of-the-art methods.

2. Related work

Person re-ID is a widely studied computer vision problem. Supervised learning is highly successful in person re-ID. Advanced techniques [29, 21, 15], e.g., attention mechanism [16, 33, 1, 34], perform well on person re-ID datasets. Meanwhile, the community also has an interest in unsupervised learning methods for person re-ID.

2.1. Unsupervised domain adaptation

Efforts have been made to develop unsupervised domain adaptation (UDA) methods for person re-ID, which transfer the learned knowledge from the labeled source domain to the unlabeled target domain [27, 3, 40, 41, 31, 5, 6, 7, 8, 35]. Generative methods, such as PTGAN [27] and SPGAN [3], transfer person images from source domain to target domain, and then use transferred images for training. Some works, such as MAR [31], MMT [7], and SpCL [8], utilize the source dataset as a reference to generate pseudo-labels, supervising the training of models. Different from these UDA works, our method uses no labeled sample yet achieves good results on par with many transfer learning methods.

2.2. Unsupervised person re-identification

There are some works focusing on unsupervised person re-ID without any labeled examples from source domain [17, 18, 25, 32]. BUC [17] and HTC [32] generated pseudo-labels by hierarchical clustering methods, and updated models with the pseudo-labels using classification loss or triplet loss. To avoid the effects of noisy pseudo-labels, MMCL [25] formulated unsupervised person re-ID as a multi-label classification problem, by maintaining a memory bank of all the instances in the dataset. Similar to MMCL, SSL [18] proposed to treat unsupervised person re-ID as a softened classification task. Our work differs with previous works as we propose a novel contrastive learning loss for unsupervised person re-ID using noisy pseudo-labels.

2.3. Contrastive learning

Contrastive learning methods [10, 2, 9] have been successful in self-supervised representation learning. These approaches learn instance-level discriminative representation by contrasting positive pair against negative pair without supervisory signals. Our work share many similarities with these state-of-the-art contrastive learning methods, in particular using views differently augmented from an image as positive pairs. Different from self-supervised representation learning that uses only a single positive, our contrastive learning framework achieves good results in person re-ID by considering more positive examples.

In the field of person re-ID, SpCL [8] also adopted a contrastive learning loss with a running hybrid memory for UDA object re-ID. SpCL proposed a hybrid memory and a self-paced clustering strategy to encode all available information from both source and target domains for feature learning with most reliable cluster centroids. In this work, we present another clustering strategy, i.e., considering and taking more neighbors as positives. Different from SpCL, this work proposes a novel contrastive learning loss and is able to handle noisy pseudo-labels without a memory bank of the entire dataset.

3. Method

3.1. The contrastive learning framework

Our method, namely Take More Positives (TMP), not only learns representations by maximizing similarity between views augmented in different ways from the same image, but also mines the relationship between samples with pseudo-labels. As the name Take More Positives suggests, considering more positive examples to model intra-class variations is an element of critical importance for unsupervised person re-ID. Algorithm 1 summarizes the proposed method. As illustrated in Figure 2, the framework comprises the following four components.

- A data augmentation module $T$ that transforms an input image $x$ into a randomly augmented view $\tilde{x}$ of the image. For each image in the original dataset, we generate two different views of the same image, represented as $\tilde{x}_i$ and $\tilde{x}_j$, respectively. In this work, we use a
Data augmentation

Encoder

Augmented views

Person images

Label generator

Pseudo-labels

Proposed contrastive loss

Figure 2: Our simple contrastive learning framework for unsupervised person re-ID. A stochastic data augmentation module is applied to each data example to obtain two views augmented in different manners from the same image. The encoder network \( f_\theta \) is used to extract features from images. Our framework explores the relationship between data examples with clustering-generated pseudo-labels \( y_i = \mathcal{G}(\tilde{x}_i) \) and the proposed contrastive learning loss.

similar set of image augmentations as in MMCL [25]. First, CamStyle [42] is adopted as a data augmentation strategy. A random patch of the image is selected and resized to \( 256 \times 128 \) with a random horizontal flip and a random rotation, followed by a random Gaussian blur. Finally, random erasing [39] is applied to the patches.

- A neural network encoder \( f \) defined by a set of parameters \( \theta \), mapping a data example to a feature \( z = f_\theta(\tilde{x}) \). We use ResNet-50 [11] as our parametric encoder \( f_\theta \). The encoder \( f_\theta \) is initialized with weights pre-trained on ImageNet. Following [21], the stride of the last spatial down-sampling operation in ResNet-50 is set to 1. The output of the final average pooling layer is passed to a batch normalization layer [13], as in [21, 25].

- A pseudo-label generator \( \mathcal{G} \) that splits the dataset into a number of clusters. We generate pseudo-labels \( y \) for instances in the dataset, i.e., \( y = \mathcal{G}(f_\theta(x)) \). Therefore, views augmented in different manners from the same image, \( \tilde{x}_i \) and \( \tilde{x}_j \), share the same pseudo-label \( y \). In this paper, we use a simple clustering algorithm DBSCAN [4, 24] as the pseudo-label generator \( \mathcal{G} \). We use Jaccard distance [38] for clustering, as in [6]. The looseness of clustering is adjusted by the maximum distance between neighbors \( \epsilon \). The unclustered instances by \( \mathcal{G} \) are treated as distinct classes.

- A contrastive learning loss \( \mathcal{L} \) for unsupervised person re-ID. It uses clustering-generated pseudo-labels to learn data distribution on the unit hypersphere. We introduce the proposed contrastive loss in the following subsection.

3.2. Contrastive loss with pseudo-labels

Given a batch of \( N \) randomly sampled images, the data augmentation module \( \mathcal{T} \) produces \( 2N \) data points. Let \( s_{i,j} \) denote the similarity of a pair of examples \( (\tilde{x}_i, \tilde{x}_j) \), calculated by the dot product between their \( \ell_2 \) normalized fea-
The contrastive loss used in self-supervised learning [10, 2] for a positive pair of examples $L_i \triangleq \mathcal{L}(\tilde{x}_i, \tilde{x}_j)$ is defined as

$$L_i = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{I}_{[k\neq i]} \exp(s_{i,k}/\tau)} ,$$  \hspace{1cm} (2)

where $\mathbb{I}_{[\cdot]}$ is an indicator function and $\tau$ denotes a temperature parameter. The final loss for optimizing $f_\theta$ is computed across all positive pairs via both $\mathcal{L}(\tilde{x}_i, \tilde{x}_j)$ and $\mathcal{L}(\tilde{x}_j, \tilde{x}_j)$ in the batch. This contrastive loss is equivalent to optimizing two metrics of the encoder network $f_\theta$: the alignment of the two augmented views of the same image and the uniformity of the representation population [26]. In other words, it acts as an instance discrimination task, which spreads instances of the same person identity apart during training, resulting in poor performance for person re-ID.

In this paper, we propose a novel contrastive learning loss with clustering-generated pseudo-labels for unsupervised person re-ID as follows:

$$L_{ij} = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{I}_{[k\neq i]} \exp(s_{i,k}/\tau)} ,$$  \hspace{1cm} (3)

$$L_i = \sum_{j=1}^{2N} \mathbb{I}_{[j\neq i]} \mathbb{I}_{y_i=y_j} L_{ij} .$$  \hspace{1cm} (4)

Similar to Equ. (2), our final loss is computed across all positive pairs in the batch. By considering more positive examples, our contrastive loss encourages the encoder to give closer aligned features to augmented views of person images that share the same pseudo-label.

### 3.3. Discussion

**Compared to hard-batch triplet loss.** Triplet loss [12, 23] is a widely used objective function in person re-ID. Within the batch, it mines the hardest positive and negative for each data point during training. Compared to the hard-batch triplet loss, our contrastive learning loss handles the entire batch and hard negatives among them by the adjustable temperature. Our empirical results in Table 4 show that contrastive loss performs better than triplet loss in unsupervised person re-ID, which is consistent with self-supervised representation learning [2].

**Take more positives.** Following self-supervised representation learning methods [10, 2, 9], we draw two differently augmented views for each image in the batch, which leads to more natural positive pairs for training than other unsupervised person re-ID methods [32, 25]. In addition, with noisy pseudo-labels, we consider more positive examples for each data point than those methods in self-supervised presentation learning.

To better understand how our framework works with noisy pseudo-labels, we implement a counterpart of our framework without label generation. We use the same architecture of encoder network $f_\theta$ and data augmentation module $T$ as TMP for the counterpart. The counterpart is trained with the contrastive loss Equ. (2) for 60 epochs. As shown in Figure 3b, without pseudo-labels, the counterpart is unable to learn identity-level discriminative representations, as the original contrastive learning loss (Equ. (2)) acts as an instance discrimination prediction task [2, 26], spreading instances of the same identity apart.

On the contrary, pseudo-labels and large batch sizes allow TMP to explore the relationship between more positive examples at a time. Although the pseudo-labels generated by clustering algorithms are noisy, learning features on the augmented views, rather than the original images, reduces the bad influence of the noisy pseudo-labels. At the same time, our framework still benefits from good instance-level representations learned in the contrastive manner.
Figure 3: Person re-ID performance on Market-1501, evaluated by Rank-1 (%) and mAP (%).

Table 1: Results of different choices of temperature $\tau$ on Market-1501.

| $\tau$ | Rank-1 | Rank-5 | Rank-10 | mAP |
|--------|--------|--------|---------|-----|
| 0.01   | 0.1    | 0.6    | 1.3     | 0.1 |
| 0.05   | 87.5   | 94.2   | 96.1    | 69.6|
| 0.1    | 84.9   | 92.8   | 95.0    | 65.5|
| 0.2    | 65.1   | 80.2   | 85.2    | 39.9|
| 0.5    | 34.4   | 53.8   | 62.7    | 13.7|

MSMT17 [27] is a large scale person re-ID dataset with data collected from 15 camera views. It comprises 126,411 person images of 4,101 person identities. The dataset suffers from variations of scene and lighting, and is more challenging than Market-1501 and DukeMTMC-reID [25], especially for unsupervised person re-ID. It contains a training set of 32,621 images and a testing set of 93,820 images.

4.2. Implementation details

Optimization. We use LARS [30] as our optimizer. The global weight decay parameter is $1.5 \times 10^{-6}$. We exclude the biases and batch normalization parameters from both LARS adaptation and weight decay as in [2, 9]. We set the base learning rate to 0.3, scaled linearly based on batch size ($LearningRate = 0.3 \times \frac{BatchSize}{256}$). We train models for 60 epochs with a cosine decay learning rate schedule [19] but no restarts, taking approximately 2 hours for Market-1501 with a batch size of 256 ($N$ in Algorithm 1) in 8 GPUs. In addition, we use a linear warmup for the first 2 epochs. For main results (see Table 7), we train models for 200 epochs.

Evaluation. For inference, we resize images to $256 \times 128$ and normalize them with RGB mean and standard deviation. We evaluate person re-ID performance on $\ell_2$ normalized features of images by cosine distance. No post-processing (i.e., re-ranking [38] and multi-query setting) is used in this work.

4.3. Parameter analysis

Temperature. Temperature $\tau$ in Eqn. (3) effectively weights different examples, and an appropriate temperature can help the model learn from hard negatives. In Table 1, we test different temperature values $\tau$ in the proposed contrastive loss. Results show that the performance is significantly worse without proper temperature scaling. Moreover, a very small temperature $\tau = 0.01$ fails to converge. In this work, we use a fixed temperature $\tau = 0.05$ for all the experiments.

Loose clustering. Distance threshold $\epsilon$ controls the looseness of clustering in label generator $\mathcal{G}$. In our experiments,
we find that a loose clustering leads to better performance as shown in Table 2. We also report the number of final clusters on the training set. Note that there are 751 person identities in the Market-1501 training set, which is close to our results with a loose clustering.

Our finding is opposed to the intuition. In other works [17, 32], clustering is always proceeded carefully. However, our framework instead achieves better clustering and person re-ID performance with a loose clustering. We argue that considering more positives based on the stochastically augmented views of images, rather than the original images, is helpful to learn better representations of identities. Moreover, contrastive learning loss with a tight clustering pushes instances away from each other (they always have different pseudo-labels when $\epsilon$ is small, as they are unable to be clustered at the start of training). As a result, instances of the same identity lose their chances to get closer. It also explains the significant drop with regard to the mAP metric subject to the small $\epsilon$, while Rank-1 accuracy descends slightly.

Larger batch size and longer training. Table 3 shows the impact of batch size when our framework is trained for 60 epochs. Larger batch sizes, which allow us to train models with more positives and negatives, have a significant advantage over small ones ($N = 64$ versus $N = 256$). However, we find that a very large batch size like 1024 instead deteriorates person re-ID performance. We argue that a large number of false negative examples are included in a batch, pushing instances of the same identity away from each other and overwhelming our framework during training, as the batch size increases.

As shown in Figure 4, changes in person re-ID performance of different batch sizes also prove our option, i.e., too many false negatives at the start overwhelm the framework. Meanwhile, with a small batch size (Figure 4a), the training takes longer to converge.

### 4.4. Ablation studies

**Objective function alternatives.** We compare the proposed contrastive loss against the widely used objective function in person re-ID, i.e., triplet loss. Hard-batch triplet loss and a PK sampling are adopted as in [32]. For a fair comparison, we use a batch size of 256 in the experiments. We also compare to the contrastive learning loss in self-supervised representation learning (i.e., Equ. (2)) [2], which means only one single positive pair is used for each image.

Results in Table 4 show that the proposed contrastive loss is able to handle noisy pseudo-labels, outperforming the common triplet loss. Compared to the original contrastive learning loss, which only uses augmented views as the single positive pair, our contrastive loss improves performance significantly with noisy pseudo-labels (see more discussion in Sec. 3.3). Therefore, the proposed contrastive learning loss is important for our framework.

**Table 2: Results of different clustering threshold $\epsilon$ on Market-1501.**

| $\epsilon$ | Rank-1 | Rank-5 | Rank-10 | mAP | clusters |
|------------|--------|--------|---------|-----|----------|
| 0.5        | 84.5   | 92.1   | 95.3    | 55.2| 1373     |
| 0.6        | 85.2   | 92.8   | 95.1    | 56.2| 1377     |
| 0.65       | 85.6   | 92.8   | 95.3    | 56.5| 1395     |
| 0.7        | 87.4   | 94.5   | 96.0    | 69.2| 833      |
| 0.75       | 87.5   | 94.2   | 96.1    | 69.6| 794      |

**Table 3: Results of different choices of batch size $N$ on Market-1501.** We train models for 60 epochs with linearly scaled learning rates.

| $N$  | Rank-1 | Rank-5 | Rank-10 | mAP |
|------|--------|--------|---------|-----|
| 64   | 78.0   | 90.2   | 92.9    | 54.8|
| 128  | 83.3   | 92.2   | 94.4    | 63.5|
| 256  | 87.5   | 94.2   | 96.1    | 69.6|
| 512  | 87.4   | 94.0   | 95.6    | 68.5|
| 1024 | 85.4   | 93.1   | 95.2    | 60.1|

**Table 4: Comparison with other loss functions on Market-1501.**

| Objective | Rank-1 | Rank-5 | Rank-10 | mAP |
|-----------|--------|--------|---------|-----|
| Triplet   | 67.1   | 79.0   | 83.5    | 36.0|
| Contrastive (single pair) | 30.9 | 52.1 | 61.5 | 11.4 |
| Ours      | 87.5   | 94.2   | 96.1    | 69.6|

**Table 5: Lesion studies on data augmentations.** Results are reported on Market-1501. $T_{tmp}$ denotes our data augmentation module. $-$: remove the specific data augmentation operation from $T_{tmp}$. $+$: add the specific data augmentation operation to $T_{tmp}$. $A \rightarrow B$: add A operation by replacing B in $T_{tmp}$.

| Objective | Rank-1 | Rank-5 | Rank-10 | mAP |
|-----------|--------|--------|---------|-----|
| $T_{tmp}$ | 87.5   | 94.2   | 96.1    | 69.6|
| $-$ CamStyle [42] | 54.9 | 65.7 | 70.4 | 33.1 |
| $-$ random erasing [39] | 82.5 | 90.8 | 93.2 | 59.9 |
| $-$ Gaussian blur | 86.6 | 93.8 | 95.6 | 68.8 |
| $-$ random horizontal flip | 83.3 | 91.9 | 94.3 | 64.9 |
| $-$ random rotation | 86.2 | 93.7 | 95.2 | 68.2 |
| $-$ random crop | 85.7 | 93.4 | 95.3 | 68.4 |
| $-$ $t' \sim T$ (single view) | 74.1 | 85.2 | 87.3 | 51.0 |
| + color jitter | 85.9 | 93.3 | 95.5 | 67.6 |
| + color jitter $\rightarrow$ CamStyle | 53.5 | 65.4 | 70.0 | 32.0 |

**Objective** | Rank-1 | Rank-5 | Rank-10 | mAP |
|--------------|--------|--------|---------|-----|
Lesion studies on data augmentation. We report lesion studies on composition of data augmentation operations \( \mathcal{T} \). To better understand the effects of individual data augmentations in unsupervised person re-ID, we evaluate the performance of our framework by removing or adding data augmentations individually in Table 5. Generally, Gaussian blur, random rotation, random horizontal flip and random crop operations have a moderate impact on unsupervised person re-ID. Random erasing [39], which works well in supervised person re-ID, is still important for achieving good performance in the unsupervised scenario.

In addition, we find that CamStyle [42] is crucial for our framework. It builds a bridge through which models are able to encode intra-class variants without ground truths. We also find that the color distortion leads to a worse performance in unsupervised person re-ID, which is different from self-supervised representation learning. We further test the effects of color distortion by replacing CamStyle with it. In terms of performance, we find that color distortion is harmful in unsupervised person re-ID. It might be because appearance is an important clue to identify person among examples.

We also report the results when only one single augmented view is used for training in Table 5. In this setting, positive examples are only provided by the noisy pseudo-labels, which hinders improvement of our framework. Overall, examples provided by our data augmentation module \( \mathcal{T} \) and the design of differently augmented views are helpful to unsupervised person re-ID.

Label generation. We replace the clustering algorithm in label generation \( \mathcal{G} \) with PUL method [5]. PUL clusters examples by k-means and only selects reliable data instances for training. In this experiment, we follow their clustering implementation (\( K = 750 \) for k-means) but treat these unreliable examples as distinct classes. By this way, we are able to train the total dataset with our contrastive learning loss. As in [5], we use cosine similarity to compute the distance between examples. Let \( \lambda \) denote the reliability threshold. Therefore, a larger \( \lambda \) means a stricter sample selection.

Results are reported in Table 6. Our framework is still effective when we use other clustering algorithms for label generation. Moreover, it is also observed that a loose clustering leads to better performance than others in our framework. As discussed above, contrastive learning loss pushes other instances away on the unit hypersphere, i.e., their cosine similarities decrease during training. With a higher \( \lambda \), examples from the same identity will have no chance to be clustered together after a number of iterations.

4.5. Comparison with state-of-the-arts

We compare TMP with the state-of-the-art unsupervised person re-ID methods including BUC [17], SSL [18], HTC [32] and MMCL [25]. Following conventional settings, we use the same architecture of the encoder network with other person re-ID works, as described in Sec. 3.1. Results are presented in Table 7. With the proposed contrastive loss, our TMP outperforms the state-of-the-art unsupervised methods with a significant advantage by taking more positives.

We also compare TMP to the state-of-the-art UDA methods in the field of person re-ID, which transfer the learned knowledge from source domain to target domain. As shown in Table 7, our unsupervised contrastive learning framework
|                  | Market-1501 | DukeMTMC-reID | MSMT17  |
|------------------|-------------|---------------|---------|
|                  | Rank-1  | Rank-5 | Rank-10 | mAP    | Rank-1  | Rank-5 | Rank-10 | mAP    | Rank-1  | Rank-5 | Rank-10 | mAP    |
| **UDA methods:** |           |           |         |        |           |           |         |        |           |           |         |        |        |
| PUL [5]          | 50.9     | 66.5     | 72.6    | 24.8   | 36.5     | 52.6     | 57.9    | 21.5   | -        | -        | -      | -      |
| SPGAN [3]        | 58.1     | 76.0     | 82.7    | 26.9   | 46.9     | 62.6     | 68.5    | 26.4   | -        | -        | -      | -      |
| HHL [40]         | 62.2     | 78.8     | 84.0    | 31.4   | 46.9     | 61.0     | 66.7    | 27.2   | -        | -        | -      | -      |
| MAR [31]         | 67.7     | 81.9     | -       | 40.0   | 67.1     | 79.8     | -       | 48.0   | -        | -        | -      | -      |
| ECN [41]         | 75.1     | 87.6     | 91.6    | 43.0   | 63.3     | 80.4     | 84.0    | 40.4   | 30.2     | 41.5     | 46.8   | 10.2   |
| SSG++ [6]        | 86.2     | 94.6     | 96.5    | 68.7   | 76.0     | 85.8     | 89.3    | 60.3   | 41.6     | -        | 62.2   | 18.3   |
| MMT [7]          | 87.7     | 94.9     | 96.9    | 71.2   | 78.0     | 88.8     | 92.5    | 65.1   | 50.1     | 63.9     | 69.8   | 23.3   |
| DG-Net++ [43]    | 83.1     | 91.5     | 94.3    | 64.6   | 75.2     | 89.2     | 90.2    | 65.2   | 51.7     | 64.0     | 68.9   | 24.3   |
| NRMT [35]        | 87.8     | 94.6     | 96.5    | 71.7   | 77.8     | 86.9     | 89.5    | 62.2   | 45.2     | 57.8     | 63.3   | 20.6   |
| MAR [20]         | 88.1     | 94.4     | 96.2    | 71.5   | 79.5     | 88.3     | 91.4    | 65.2   | 51.7     | 64.0     | 68.9   | 24.3   |
| JVTC+ [14]       | 86.8     | 95.2     | 97.1    | 67.2   | 80.4     | 89.9     | 92.2    | 66.5   | 52.9     | 70.5     | 75.9   | 27.5   |
| SpCL [8]         | 89.7     | 96.1     | 97.6    | 77.5   | -        | -        | -       | -      | 53.7     | 65.0     | 69.8   | 26.8   |
| **Unsupervised methods:** |           |           |         |        |           |           |         |        |           |           |         |        |
| BUC [17]         | 66.2     | 79.6     | 84.5    | 38.3   | 47.4     | 62.6     | 68.4    | 27.5   | -        | -        | -      | -      |
| SSL [18]         | 71.7     | 83.8     | 87.4    | 37.8   | 52.5     | 63.5     | 68.9    | 28.6   | -        | -        | -      | -      |
| HTC [32]         | 80.0     | 91.6     | 95.2    | 56.4   | 69.6     | 83.4     | 87.4    | 50.7   | -        | -        | -      | -      |
| MMLC [25]        | 80.3     | 89.4     | 92.3    | 45.5   | 65.2     | 75.9     | 80.0    | 40.2   | 35.4     | 44.8     | 49.8   | 11.2   |
| **Ours:**        |           |           |         |        |           |           |         |        |           |           |         |        |
| TMP (N = 256, 60 epochs) | 87.5    | 94.2     | 96.1    | 69.6   | **73.2** | 82.9     | 86.1    | **53.2** | 37.2     | 46.1     | 53.7   | 13.9   |
| TMP (N = 256, 200 epochs) | **88.3** | **94.6** | **96.3** | **70.4** | 72.4     | 81.2     | 84.7    | 51.6   | **40.4** | **53.0** | 59.8   | **17.3** |

Table 7: Comparison with the state-of-the-art methods in unsupervised person re-ID. We also compare our method to the state-of-the-art UDA methods, which use labeled examples from source domain for training. For these UDA methods, we present their best results on target datasets, regardless of source dataset used for training.

outperforms many transfer learning methods, being close to top UDA results.

5. Conclusions

Unsupervised learning is closing the performance gap with supervised methods in many fields of computer vision. In this paper, we present a simple and effective framework for unsupervised person re-ID. The strength of our framework suggests that, despite the noisy pseudo-labels, considering more positive examples is still beneficial to mimic the relationship of person images with our novel contrastive learning loss in the unsupervised scenario. We hope that our work could inspire further research on unsupervised person re-ID and even other unsupervised computer vision tasks, such as person search [37, 28].

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