SSKD: Self-Supervised Knowledge Distillation for Cross Domain Adaptive Person Re-Identification

Junhui Yin, Jiayan Qiu, Siqing Zhang, Zhanyu Ma*, Jun Guo

Abstract

Domain adaptive person re-identification (re-ID) is a challenging task due to the large discrepancy between the source domain and the target domain. To reduce the domain discrepancy, existing methods mainly attempt to generate pseudo labels for unlabeled target images by clustering algorithms. However, clustering methods tend to bring noisy labels and the rich fine-grained details in unlabeled images are not sufficiently exploited. In this paper, we seek to improve the quality of labels by capturing feature representation from multiple augmented views of unlabeled images. To this end, we propose a Self-Supervised Knowledge Distillation (SSKD) technique containing two modules, the identity learning and the soft label learning. Identity learning explores the relationship between unlabeled samples and predicts their one-hot labels by clustering to give exact information for confidently distinguished images. Soft label learning regards labels as a distribution and induces an image to be associated with several related classes for training peer network in a self-supervised manner, where the slowly evolving network is a core to obtain soft labels as a gentle constraint for reliable images. Finally, the two modules can resist label noise for re-ID by enhancing each other and systematically integrating label information from unlabeled images. Extensive experiments on several adaptation tasks demonstrate that the proposed method outperforms the current state-of-the-art approaches by large margins.

Introduction

The motivation of person re-identification (re-ID) is to find a target person’s images in one camera from the gallery images obtained by other different cameras. While person re-ID in fully-supervised manner has shown great progress given the recent advances of convolutional neural network (Luo et al. 2019), person re-ID in unsupervised domain adaptation (UDA) is still a challenging task. The key problem is that UDA models in person re-ID suffer from domain gap when it transfers knowledge from the labeled source domain to the unlabeled target domain. This domain discrepancy is generally due to the data-bias existing between source data and target data.

Recently, various methods (Song et al. 2018, Fu et al. 2019, Zhang et al. 2019, Yang et al. 2020, Ge, Chen, and Li 2020) have been proposed to alleviate this issue. These works mainly focus on pseudo label generation of unlabeled target domain. The clustering-based adaptation method (Song et al. 2018) first extend existing UDA theories to person re-ID tasks and employ unsupervised clustering methods (e.g., k-means) to predict pseudo labels for unlabeled target data. SSG (Fu et al. 2019) mines the potential similarity of unlabeled samples to automatically separate unlabeled data into different clusters, and then each cluster is labeled with pseudo identity. These methods usually treat pseudo labels as ground truth labels to optimize the model, which indicates that their performance highly relies on the clustering accuracy. However, most clustering methods can’t guarantee clustering accuracy even with modern approaches. Based on this, the self-training (Zhang et al. 2019) considers different learning strategies to improve the quality of labels by exploiting complementary data information. Given that some clustering algorithms (e.g., DBSCAN) directly regard
low confidence samples as outliers and give them up during training. ACT (Yang et al. 2020) designs two models to promote each other with noisy pseudo labels. Furthermore, mutual mean-teaching (Ge, Chen, and Li 2020) is proposed to reduce the effects of noisy labels in a collaborative training manner, which defines identities by off-line and on-line refined pseudo labels.

Despite promising results achieved by recent works, the performances of these UDA approaches is still not satisfactory enough (e.g., the current best performance on the Market1501 dataset is much lower than its supervised counterparts). The main reason is that most existing methods focus on the clustering quality but ignoring the potential information existing in the unlabeled images. During the clustering process, different images of the same identity might be separated into different clusters, which generates the wrong pseudo identities. One reason of this misclassification is that the pseudo labels are predicted by the knowledge learned from the different domain. Another reason is that the task itself brings large noise to the data. As shown in the Figure 1, different pedestrians under the same camera may wear similar clothes, while the same person will appear under different cameras for the re-ID task. To further improve the quality of labels and mine the potential information of unlabeled images, we propose to learn different representations by exploiting differently augmented views (e.g., different crops) of the same image via self-supervised learning (He et al. 2020; Chen et al. 2020) in the latent space. More specifically, to extend the framework of the re-ID task for exploiting the potential similarity of unlabeled data, we reformulate our main task as an UDA problem by combining the traditional clustering algorithm with soft label learning, where soft label reflects the image similarity and it can capture obvious similarities among semantic categories in a smooth way.

Recently, BNM (Cui et al. 2020) shows progress in boosting model learning capabilities by reducing ambiguous predictions equipped with maximizing the batch nuclear-norm on the prediction output matrix, especially in the case of insufficient labels. However, re-ID models in UDA also suffer from insufficient learning scenarios. Therefore, we update BNM to a self-supervised manner to perceive multiple prediction discriminability and diversity. To this end, we propose Self-Supervised Knowledge Distillation (SSKD), containing two key components: 1) Identity learning, which mines the relationship between unlabeled samples and predicts their one-hot labels by clustering. 2) Soft label learning, which considers labels as a distribution and employs these self-supervised soft labels, obtained from a momentum-based moving average network rather than a self-supervised pretext task, as an auxiliary information to help extracting richer knowledge from the same image’s other views. More specifically, identity learning utilizes explicit labels as supervised signals to induce images belonging to an exact class when more confidently labelled samples are incorporated in a progressive way. Given that domain shift or camera variance in training images may degrade the CNN feature representation capability, we introduce multiple peer models on unseen target domain to distill a powerful model by self-supervised learning. This self-supervised learning trains a network with soft label, which can be regarded as a gentle constraint to further enhance the robustness of category prediction against outliers. Finally, we only keep one network in the inference stage without additional computing resources or trainable parameters. Through BNM with identity learning and soft label learning, SSKD can jointly motivate an image to be related to several classes for alleviating the noisy identities produced by clustering and further strengthen the robustness of prediction on categories without extra guidance, as shown in Figure 2. To support our claims, we evaluate our approaches on four unsupervised domain adaptation tasks (e.g., Duke-to-Market). By exploiting unlabeled target dataset with SSKD, our method outperforms the current state-of-the-art approaches by large margins.

In summary, our main contributions are three-fold:

- We develop an UDA re-ID framework with progressive augmentation to combine the identity learning with the soft label learning, which can induce more confidently labelled images belonging to an exact class and motivate the low-confident samples to be associated with several related classes for alleviating the noisy identities.
- We update BNM to a self-supervised manner to better mine the fine-grained characteristics existing in the different augmented views of the same image and enhance the robustness of prediction on categories without access to the target labels.
- SSKD utilizes multiple neural networks that interact and learn from each other. In particular, the slowly evolving networks is a core to obtain self-supervised soft label. In the reference phase, only a powerful model is kept without additional computing resources or trainable parameters. In addition, our approach significantly outperforms the state-of-the-art method by large margins.

Related Work

Cross domain adaptation person re-ID. Existing studies in UDA re-ID can be mainly summarized into two categories of methods. The first category of distribution aligning learns domain-invariant features to overcoming domain discrepancy between different datasets on image-level (Deng et al. 2018; Wei et al. 2018; Bak, Carr, and Lalone 2018) and attribute-level (Wang et al. 2018; Liu et al. 2019; Chen, Zhu, and Gong 2019). FDA-Net (Li et al. 2019) further explores CycleGAN (Zhu et al. 2017) or StarGAN (Choi et al. 2018) as a style transformer to improve the discriminative capacity of model by aligning the distribution shift of two domains. Another line of methods is to exploit the underlying relations among unlabeled images and generate pseudo labels based on clustering (Fu et al. 2019; Yang et al. 2020; Ge, Chen, and Li 2020). Recently, AD-Cluster (Zhai et al. 2020) enhances the model discriminative capacity on unlabeled domain by alternating clustering and sample generation in a min-max optimization scheme. However, these works suffer from the problem of the wrong pseudo labels, which produced by clustering and noisy data.

Knowledge distillation. Knowledge distillation is an important technique to learn a smaller network with better inference efficiency from a larger network with better qual-
Figure 2: The diagram of the proposed self-supervised knowledge distillation (SSKD). During training, unlabeled images are augmented three times to obtain different views of the same images, which are fed-forward into the neural network to explore multiple similarities between them via $L_{MS}$. Subsequently, identity learning and soft label learning are designed to optimize the network with one-hot label and soft label, respectively. The model further enhances the discriminability and diversity of category prediction by performing $L_{BNM}$ on batch classification response matrix.

The Proposed Approach

Re-ID models have the basic discriminative ability for adaptation by training model with labeled source domain. Our goal is to learn more fine-grained details from unlabeled target images for knowledge transfer between different models, thus we need to first mining potential characteristics. Given a batch of images, each image is augmented three times to create three views of the same sample. Next, we employ the multi-similarity loss (Wang et al. 2019) to exploit the multiple similarities for the representation features

Learning with noisy data. Recently, training network model on noisy data has received extensive attention. Related approaches can be divided into two categories, which contains robust loss function (Ghosh, Kumar, and Sastry 2017) and the training strategies (Zhang et al. 2019; Yang et al. 2020). Some robust loss functions are designed for training model with noisy data, for example, mean absolute error loss (Ghosh, Kumar, and Sastry 2017) and generalized cross entropy loss (Zhang and Sabuncu 2018). However, these methods could not be directly used for UDA person re-ID. Some training strategies are proposed for re-ID task. PAST (Zhang et al. 2019) is consisted of conservative stage and promoting stage to select high confidence training samples. ACT (Yang et al. 2020) can not only select possibly clean samples, but also design different data flow for two networks. In this work, we develop two modules, IL and SLL, to resist noisy labels for re-ID task by enhancing each other and systematically integrating label information from unlabeled images.
in the latent space. Furthermore, we maximize agreement between different augmented views of the same image by self-supervised learning. Finally, we extend BNM to our work for strengthening the robustness and diversity of prediction on categories in a self-supervised manner.

**Preliminary.** For unsupervised domain adaptation (UDA) in person re-ID, we define the source domain data as $S = \{(x_{s,i}, y_{s,i})\}_{i=1}^{n_s}$, where $n_s$ is the number of person images in the source domain and each image $x_{s,i}$ is associated with an identity label $y_{s,i}$. Similarly, let $T$ denote a target domain containing $n_t$ unlabeled images $\{(x_{t,i})\}_{i=1}^{n_t}$.

**Supervised Learning for Source Model**

The identity information of source domain is available, thus the training process of the source data can be treated as a conventional classification problem (Zheng, Yang, and Hauptmann 2016). Source model is optimized by minimizing the cross entropy loss,

$$L_{src} = -\frac{1}{n_s} \sum_{i=1}^{n_s} \log p(y_{s,i}|x_{s,i}),$$

where $n_s$ is the number of images in source domain, $p(y_{s,i}|x_{s,i})$ is the predicted probability of image $x_{s,i}$ belonging to the identity $y_{s,i}$. At this time, the model has a certain adaptability for cross domain.

**Self-Supervised Knowledge Distillation**

**Image augmentation.** To obtain the cross views of feature representation and prediction results, each image $x_{t,i}$ is augmented three times using random crop, random horizontal flip, and random erasing (Zhong et al. 2020), creating three views of the same image, $x_{t,3i+1}$, $x_{t,3i+2}$ and $\tilde{x}_{t,3i+3}$. The three images are further encoded via three encoder networks with the same architecture, referred to as student models, to generate representation features $h_{t,3i+1}$, $h_{t,3i+2}$ and $h_{t,3i+3}$. These feature encoders are driven to perceive subtle differences of natural characteristic and semantic information among different augmented views which is essential for the representation of precise fine-grained details.

**Multi-similarity learning.** After obtaining the representation features in the embedding space, we further explore full pair-wise relations between samples in a mini-batch. Triplet loss (Hoffer and Ailon 2015) and contrastive loss (Hadsell, Chopra, and LeCun 2006) are not sufficient to pull similar samples and repel dissimilar ones for re-ID task. These approaches focus on either cosine similarities or relative similarities. To exploit the multiple similarities for the representation features of augmented views of different images, we employ the multi-similarity loss (Wang et al. 2019), implemented by two iterative steps with sampling and weighting, for pair weighting in the representation space. This allows it to compare the representation of an augmented view with other negative samples, providing a more principled method for mining the fine-grained details existing in the differently augmented views of samples.

Let the similarity of two features be $S_{ij} = \langle h_{t,i}, h_{t,j} \rangle$, where $\langle \cdot, \cdot \rangle$ defines dot product, yielding a similarity matrix $S$ whose element at $(i, j)$ is $S_{ij}$. Multi-similarity (MS) loss is formulated as,

$$L_{MS} = -\frac{1}{n_t} \sum_{i=1}^{n_t} \frac{1}{\alpha} \log[1 + \sum_{k \in P_i} e^{-\alpha(S_{ik} - \lambda)}] + \frac{1}{\beta} \log[1 + \sum_{k \in N_i} e^\beta(S_{ik} - \lambda)],$$

where $n_t$ is the number of images in target domain, and $\alpha, \beta$ are hyper-parameters as in (Wang et al. 2019).

**Identity learning.** Aiming at aggregating the information from different augmented views of the same image, we design a fusion operation to generate an individual class for each training image. To learn richer representations, the operation should effectively confuse different features, while preserving the distinctive information. Under this principle, we sum three features and then average them, formulated as,

$$h_{t,i} = \frac{1}{3} \sum_{j=1}^{3} h_{t,3i+j}, i = 1, 2, \cdots, n_t.$$ (3)

Based on these fused features, we perform clustering algorithm (Ester et al. 1996) on them, which leads to every person image assigned with a pseudo label according to clustering results. As a result, we can establish the pseudo label for each image and the number of person identities, denoted as $\tilde{y}_{t,i}$ and $m_t$ respectively. The k-th network model $f(\cdot|\theta_k)$ is updated by optimizing a cross entropy loss with label smoothing, defined as

$$L_{id}^k = -\frac{1}{n_t} \sum_{i=1}^{n_t} \sum_{j=1}^{m_t} q_j \log p_j(x_{t,i}|\theta_k),$$

where $q_j = 1 - \varepsilon + \frac{\varepsilon}{m_t}$ if $q_j = \tilde{y}_{t,i}$, otherwise $q_j = \frac{\varepsilon}{m_t}$. The overall loss for identity learning can be expressed as $L_{id} = \sum_{k=1}^{3} L_{id}^k$. Comparing with cross entropy loss, $L_{id}$ replace the original label distribution with a mixture of the label distribution and the uniform distribution, leading to label-smoothing regularization.

**Self-supervised Learning.** Due to the domain gap, the pseudo identities generated by clustering suffer from noises. Instead of the clustering-based method treating reliable samples as the same cluster for training, we propose a soft label learning, a complementary part of identity learning, that
Table 1: Comparison with state-of-the-art methods on Dukemtmc-reID (Duke) and Market-1501 (Market) for domain adaptive tasks.

| Methods     | Duke → Market | Market → Duke |
|-------------|---------------|---------------|
|             | mAP | top-1 | top-5 | top-10 | mAP | top-1 | top-5 | top-10 |
| PUL         | 20.5 | 45.5 | 60.7 | 66.7 | 16.4 | 30.0 | 43.4 | 48.5 |
| TJ-AIDL     | 26.5 | 58.2 | 74.8 | 81.1 | 23.0 | 44.3 | 59.6 | 65.0 |
| SPGAN       | 22.8 | 51.5 | 70.1 | 76.8 | 22.3 | 41.1 | 56.6 | 63.0 |
| HHL         | 31.4 | 62.2 | 78.8 | 84.0 | 27.2 | 46.9 | 61.0 | 66.7 |
| UCDA        | 30.9 | 60.4 |   -  |   -  | 31.0 | 47.7 |   -  |   -  |
| PDA-Net     | 47.6 | 75.2 | 86.3 | 90.2 | 45.1 | 63.2 | 77.0 | 82.5 |
| CR-GAN      | 54.0 | 77.7 | 89.7 | 92.7 | 48.6 | 68.9 | 80.2 | 84.7 |
| PCB-PAST    | 54.6 | 78.4 |   -  |   -  | 54.3 | 72.4 |   -  |   -  |
| SSG         | 58.3 | 80.0 | 90.0 | 92.4 | 53.4 | 73.0 | 80.6 | 83.2 |
| ECN++       | 63.8 | 84.1 | 92.8 | 95.4 | 54.6 | 74.0 | 84.7 | 89.4 |
| MMCL        | 60.4 | 84.4 | 92.8 | 95.0 | 51.4 | 72.4 | 82.9 | 85.0 |
| SNR         | 61.7 | 82.8 |   -  |   -  | 58.1 | 76.3 |   -  |   -  |
| AD-Cluster  | 68.3 | 86.7 | 94.4 | 96.5 | 54.1 | 72.6 | 82.5 | 85.5 |
| MMT         | 71.2 | 87.7 | 94.9 | 96.9 | 65.1 | 78.0 | 88.8 | 92.5 |
| DG-Net++    | 61.7 | 82.1 | 90.2 | 92.7 | 63.8 | 78.9 | 87.8 | 90.4 |
| MEB-Net     | 76.0 | 89.9 | 96.0 | 97.5 | 66.1 | 79.6 | 88.3 | 92.2 |
| Ours        | 78.7 | 91.7 | 97.2 | 98.2 | 67.2 | 80.2 | 90.6 | 93.3 |

We captures obvious similarities among semantic categories in a smooth way. It is important to note that the soft similarity is not learned from explicit guidance, but from the visual data itself. Specifically, the encoded representations are fed into a linear transformation network (a projection head), resulting in the soft pseudo labels \( z_{k,3i+k} \) for data \( x_{i,i} \) with the \( k-th \) encoder network. The proposed learning procedure can be regarded as discriminative perception based on a probability \( \mathbf{p}^{c}_{3i+k} \) of which the input image belongs to class \( c \),

\[
p_{3i+k}^{c} = \frac{\exp(z_{k,3i+k}^c)}{\sum_{c=1}^{C} \exp(z_{k,3i+k}^c)},
\]

where \( z_{k,3i+k}^c \) is the \( c-th \) output of the \( k-th \) projection head.

**Momentum update.** When the above class predictions are directly served as soft labels to supervise another peer network, we obtain poor results in experiments. Such case is caused by the rapidly changing encoder that produces an error amplification. To enhance the model predictions’ consistency, we propose a momentum-based moving average average model for each peer network. Formally, let the parameter of encoder network \( f_k \) be \( \theta_k \). The temporal average model is updated by

\[
\theta_{k,e}^{(t)} \leftarrow \rho \theta_{k,e}^{(t-1)} + (1 - \rho) \theta_k,
\]

where \( \rho \in [0, 1) \) is a momentum coefficient, \( t \) is the current iteration, and the initial temporal average parameters \( \theta_{k,e}^{(0)} \) are \( \theta_k \).

Next, we employ the one network’s past evolving model to generate supervised signals for training the other network. As shown in Figure 3, the soft label supervision are generated by the three slowly evolving models as \( p_1(f(x_{3i+1}^{th}, \theta_{i,1})), p_2(f(x_{3i+2}^{th}, \theta_{i,2})), \) and \( p_3(f(x_{3i+3}^{th}, \theta_{i,3}))) \) respectively. The distillation loss with soft label for each network are defined as

\[
L_{dt}^1(\theta_1 | \theta_3) = \frac{1}{n_t} \sum_{t=1}^{n_t} p_3(f(x_{3i+3}^{th}, \theta_{i,3}))) \log p_1(f(x_{3i+1}^{th}, \theta_{i,1})),
\]

\[
L_{dt}^2(\theta_2 | \theta_1) = \frac{1}{n_t} \sum_{t=1}^{n_t} p_1(f(x_{3i+1}^{th}, \theta_{i,1}))) \log p_2(f(x_{3i+2}^{th}, \theta_{i,2})),
\]

\[
L_{dt}^3(\theta_3 | \theta_2) = \frac{1}{n_t} \sum_{t=1}^{n_t} p_2(f(x_{3i+2}^{th}, \theta_{i,2}))) \log p_3(f(x_{3i+3}^{th}, \theta_{i,3}))).
\]

The overall distillation loss is

\[
L_{dt} = L_{dt}^1(\theta_1 | \theta_3) + L_{dt}^2(\theta_2 | \theta_1) + L_{dt}^3(\theta_3 | \theta_2).
\]

**Prediction discriminability and diversity.** During training, we want the network could not only predict training samples into reliable classes, but make it acceptable to have a certain ability of prediction discriminability and diversity. BNM (Cui et al. 2020) is proposed to boost the model learning capability under label insufficient scenarios by reducing the ambiguous predictions. Due to its simplicity and effectiveness, BNM is adopted in our work to enhance the discriminability and diversity of the model. Formally, given a mini batch data with \( B \) randomly selected unlabeled images, we define the number of classes as \( C \) and introduce the batch prediction output matrix as \( A \in \mathbb{R}^{B \times C} \) whose element at \((i,j)\) is \( a_{ij} \),

\[
\sum_{j=1}^{C} a_{ij} = 1, \forall i \in 1, \cdots, B,
\]

\[
a_{ij} \geq 0, \forall i \in 1, \cdots, B, j \in 1, \cdots, C.
\]

After taking model predictions as pseudo identities, we further strengthen the robustness of prediction on categories...
without any extra guidance, using the nuclear-norm maximization of batch classification response matrix. Actually, stronger robustness means less uncertainty in the prediction. This achieved by optimizing the following loss of BNM.

\[
L_{BNM} = \sum_{k=1}^{3} \| A_k \|_* + \sum_{k=1}^{3} \| A_{k,e} \|_*. \tag{9}
\]

Here \( A_k \) and \( A_{k,e} \) stand for the \( k \)-th network model and its past evolving model respectively. \( \| \cdot \|_* \) presents the the calculation of nuclear-norm, which is referred as (Cui et al. 2020).

Overall loss. By adding the cross entropy loss \( L_{id} \), the distillation loss \( L_{dt} \), and the BNM loss \( L_{BNM} \) into Eq. (2), the complete loss of our final proposed Self-Supervised Knowledge Distillation (SSKD) can be expressed as

\[
L = \xi L_{id} + (1 - \xi) L_{dt} + \lambda L_{BNM} + \eta L_{MS}, \tag{10}
\]

where \( \xi \in (0, 1) \) controls the importance of IL and SSL, and \( \lambda, \eta \) are weighting parameters. The main training process are shown in Algorithm 1, which can be found in supplementary.

### Experimental results and discussions

#### Experiment setting

**Datasets and evaluation metrics.** We conduct experiments on three common datasets: Market-1501 (Zheng et al. 2015), DukeMTMC-reID (Ristani et al. 2016), and MSMT17 (Ristani et al. 2016). The proposed method is evaluated on four cross domain person Re-ID tasks, which contains Duke-to-Market, Market-to-Duke, Duke-to-MSMT, and Market-to-MSMT. The mean Average Precision (mAP) and Cumulative Matching Characteristic (CMC) curve are adopted as the evaluation metrics.

**Implementation details.** Random cropping, flipping and random erasing (Zhong et al. 2020) are employed as the data augmentation. We adopt ResNet-50 (He et al. 2016) as the backbone of our model with the last classification layer removed, and initialize it by the ImageNet (Deng et al. 2009) pretrained model. DBSCAN (Ester et al. 1996) is used for clustering before each epoch. We choose the hyper-parameters (e.g., \( \xi, \lambda, \eta \)) according to the validation set of the Duke-to-Market adaptation and directly apply them to other three cross domain re-ID tasks. For more experiment details, please refer to the supplementary.

#### Comparison with state-of-the-arts

We compare our proposed approach with existing techniques on three benchmarks and give the results in Table 1 and Table 2. Our models achieve state-of-the-art (SOTA) performance in several adaptation tasks.

**Dukemtmc-reID and Market-1501.** Table 1 reports the quantitative evaluation results on the Dukemtmc-reID and Market-1501. Our SSKD achieves an mAP of 78.7% and a top-1 accuracy of 91.7% for the Duke-to-Market, which surpasses the state-of-the-art method (MEB-Net) by large margins (2.7% for mAP and 1.8% for top-1). Similar results can be observed in another adaptation task. The proposed method obtains an mAP of 67.2% and a top-1 accuracy of 80.2% for Market-to-Duke, and achieves new state-of-the-art accuracy compared with the current techniques. Moreover, our method does not explore how to manually specify the number of identities in the training set of unlabeled target data, comparing with the current best methods (MMT and MEB-Net).

#### Table 2: Comparison of proposed method with state-of-art unsupervised domain adaptive person re-ID methods on MSMT17 dataset.

| Method   | Source Dataset | Target Dataset | mAP | top-1 | top-5 | top-10 |
|----------|----------------|----------------|-----|------|------|-------|
| PT-GAN   | CVPR'18        | MSMT           | 3.3 | 11.8 | -    | 27.4  |
| SSG      | ICCV'19        | MSMT           | 13.3| 32.2 | -    | 51.2  |
| ECN++    | TPAMI'20       | MSMT           | 16.0| 42.5 | 55.9 | 61.5  |
| MMCL     | CVPR'20        | MSMT           | 16.2| 43.6 | 54.3 | 58.9  |
| DG-Net++ | ECCV'20        | MSMT           | 22.1| 48.8 | 60.9 | 65.9  |
| MMT      | ICLR'20        | MSMT           | 23.3| 50.1 | 63.9 | 69.8  |

**Ours**

| Method   | Source Dataset | Target Dataset | mAP | top-1 | top-5 | top-10 |
|----------|----------------|----------------|-----|------|------|-------|
| PT-GAN   | CVPR'18        | MSMT           | 2.9 | 10.2 | -    | 24.4  |
| SSG      | ICCV'19        | MSMT           | 13.2| 31.6 | -    | 49.6  |
| ECN++    | TPAMI'20       | MSMT           | 15.2| 39.4 | 53.1 | 58.7  |
| MMCL     | CVPR'20        | MSMT           | 15.1| 39.8 | 51.8 | 56.7  |
| DG-Net++ | ECCV'20        | MSMT           | 22.1| 48.4 | 60.9 | 66.1  |
| MMT      | ICLR'20        | MSMT           | 22.9| 49.2 | 63.1 | 68.8  |

**Ours**

| Method   | Source Dataset | Target Dataset | mAP | top-1 | top-5 | top-10 |
|----------|----------------|----------------|-----|------|------|-------|
| PT-GAN   | CVPR'18        | MSMT           | 23.8| 49.6 | 63.1 | 68.8  |

**MSMT17.** Our proposed method is also evaluated on a larger and more challenging dataset (MSMT17). From experimental results in Table 2, it can be observed that the proposed method clearly outperforms other methods when Dukemtmc-reID and Market-1501 are employed as source domains. For instance, with Dukemtmc-reID as source domain, our approach improves the accuracy by more than 2.5 percentage points over the state-of-the-art accuracy of mAP. Our method has better performance than other existing techniques on all experiments, which further demonstrates the validation of our proposed method. More importantly, our method almost approaches the performances of supervised learning (Luo et al. 2019) without any auxiliary information on the target domain.

#### Ablation Study

Our proposed framework achieves new SOTA performance by using SSKD. To claim the effectiveness of each component in our framework, extensive ablation experiments are conducted under different settings.

**Identity learning.** We propose the identity learning (IL) to predict the ground truth classes for high-confident samples, which preserve the most reliable clusters for providing stronger supervision. To verify the effectiveness of such a learning manner, we evaluate our framework when removing it. The considerable degrades (e.g., from 78.7% to 51.3%) for mAP in Table 3 are observed under this setting (SSKD without any extra guidance).
(w/o $L_{id}$), especially for Duke-to-Market adaptation. This indicates the importance of adopting the identity learning.

**Soft label learning.** As a complementary component of identity learning, soft label learning (SLL) can regard labels as a distribution and enhance the robustness of category prediction. As in Table 3 on Duke-to-Market task, our SSKD beats SSKD (w/o $L_{id}$) by 78.7 and 91.7 percentage points on mAP and top-1 respectively. Similarly, for Market-to-Duke, obvious drops on mAP and top-1 are 1.5% and 1.6%, respectively. The large performance gaps demonstrate the effectiveness of the SLL module. Without SLL, images of the same identity from noisy samples are hard to be selected as reliable images because of domain shift and camera variance. In addition, invariance learning has an important effect in this training process by using the momentum update mechanism. We also demonstrates the importance of adopting the momentum update mechanism, which can be referred in the supplementary.

**Multi-similarity learning.** To investigate the impact of multi-similarity loss, we evaluate the performance of our method without multi-similarity learning (MSL). This modification brings the distinct drops of the performance, e.g., with an over 3% decrease of mAP on Market-to-Duke. MSL allows us to mining the fine-grained details existing in the differently augmented views of the same image. It can integrate the three similarities effectively into a single framework by using only one loss function.

**Insufficient learning scenarios.** Our learning task is an unsupervised open-set domain adaptation, where some labels are insufficient and even unseen. The methods without the BNM loss result in lower performances. We could see the significant progress and benefit of BNM to our re-ID tasks.

**Parameter Analysis**

To analyze the effect of different hyper-parameters on adaptation re-ID task, we conduct some comparative experiments by changing the value of one parameter and keep the others fixed. We choose the hyper-parameters on Duke-to-Market task and directly apply them to other three adaptation tasks.

**The impact of the hyper-parameter $\xi$.** We first investigate the impact of the hyper-parameter $\xi$ that balances the effect of the explicit classes and the reliable classes. As shown in Figure 4 when $\xi$ approaches 0 and 1, the model performance continue decreasing. At this time, the model reduces to IL and SLL respectively. The model achieves optimal performances when $\xi = 0.5$. The reason is that the weight factor better balances two modules and induces model to predict ground truth classes for clean label and soft similarity for noisy label in a progressive way.

**The impact of the hyper-parameter $\lambda$ and $\eta$.** Figure 4 shows how the re-ID performance varies with different values of $\lambda$ and $\eta$, weight factors for BNM and MS losses. When $\lambda$ increases from 0.5 to 1.5, the re-ID performance has a slight increase. When $\lambda$ continually gets larger, we observe a slight decrease on re-ID performance. The weight factor $\eta$ also has the similar result, which further indicates that our method is robust and insensitive to different parameters. Finally, the proposed framework obtains the best result with $\xi = 0.5$, $\lambda = 1.5$, and $\eta = 3$ on Duke-to-Market transfer.

**Conclusions**

In this work, we introduce a novel approach to effectively exploit the potential similarity of unlabeled data to boost performance for cross domain person re-ID task without target labels. To alleviate the problem of noisy labels produced by clustering, we propose **Self-Supervised Knowledge Distillation (SSKD)** to jointly motivate an image to be related to several classes and enhance the robustness of category prediction by two key components: identity learning and soft label learning. The experimental results indicate that the proposed method achieves new SOTA performances on three challenging datasets. In addition, we do not increase additional computing resources or trainable parameters in inference stage.
Appendix

In the supplementary material, we would like to show more details about implementation detail and experimental results.

Experiment detail

Random cropping, flipping and random erasing [Zhong et al. 2020] are employed as the data augmentation. We adopt ResNet-50 [He et al. 2016] as the backbone of our model with the last classification layer removed, and initialize it by the ImageNet (Deng et al. 2009) pretrained model. DBSCAN [Ester et al. 1996] is used for clustering before each epoch. We choose the hyper-parameters (e.g., $\xi$, $\lambda$, $\eta$) according to the validation set of the Duke-to-Market adaptation and directly apply them to other three cross domain re-ID tasks. Specifically, the overall learning process can be trained by two stages: supervised learning for source model and domain adaptation stage. The main training process is shown in Algorithm 1.

Supervised learning for source model. We first pre-train three source models on the source dataset in a supervised manner. These three models has the same architecture: ResNet-50, and are initialized by using parameters pre-trained on the ImageNet. The networks parameters $\theta_1$, $\theta_2$, and $\theta_3$ are optimized independently by minimizing loss. ADAM is employed as our optimizer. We also utilize a mini-batch size of 64 in 4 GPUs, and set an initial learning rate of 0.00035. Finally, 80 epochs are trained with the learning rate multiplied by 0.1 at 40 and 70 epochs.

Cross domain adaptation. Based on the pre-trained network parameters, we update the three networks by optimizing the overall loss with the selected hyper-parameters $\xi = 0.5$, $\lambda = 1.5$, and $\eta = 3$. In addition, we also follow the same data augmentation strategy. All the networks are trained for 40 epochs, using ADAM optimizer with learning rate of 0.00035, momentum of 0.0005 and batch size of 64. In each epoch, we use DBSCAN for clustering. It is noted that only one model is kept during test.

Momentum update mechanism. The motivation behind SSKD is that we generate self-supervised labels for one student model with the prediction outputs from another network model, leading to transferring rich structured knowledge between different models. Invariance learning has an important effect in this training process by using the momentum update mechanism. To verify its effect, we use one network’s current-iteration predictions as pseudo labels and remove the nuclear-norm maximization of batch classification response matrix in the slowly evolving networks. Such experiments are denoted as SSKD (w/o $\theta_{\cdots}$). The large margin of performance declines (e.g., from 78.7% to 46.3% for mAP) can easily be observed in Table 3 which demonstrates the importance of adopting the momentum update mechanism.

References

Ahn, S.; Hu, S. X.; Damianou, A.; Lawrence, N. D.; and Dai, Z. 2019. Variational information distillation for knowledge transfer. In CVPR.

Algorithm 1 SSKD’s main training process.

Require: Source domain data: $S = \{(x_{s,i}, y_{s,i})|_{i=1}^{n_s}\}$, target domain data: $T = \{(x_{t,i})|_{i=1}^{n_t}\}$, batch size $B$.

Ensure: The powerful model parameter.

1: Initialize the parameters of encoder networks by optimizing with Eq. (1) on $S$.
2: Draw three augmentation functions $\psi_j \sim \Psi$, $j = 1,2,3$.
3: for sampled batch $\{x_{i,j}|_{j=1}^{B}\}$ do
4:     for $i \in \{1, \cdots, B\}$ do
5:         # the augmentation
6:         $\bar{x}_{t,3i+j} = \psi_j(x_{t,3i+j})$, $j = 1,2,3$.
7:         # representation
8:         $h_{t,3i+j} = f_j(h_{t,3i+j})$, $j = 1,2,3$.
9:         # projection
10:        $z_{t,3i+j} = g_j(h_{t,3i+j})$, $j = 1,2,3$.
11:     end for
12:     Update peer moving average models by Eq. (5).
13:     Update peer models by optimizing the objective function Eq. (10).
14: end for
15: Return the powerful model parameters.

Bak, S.; Carr, P.; and Lalonde, J.-F. 2018. Domain adaptation through synthesis for unsupervised person re-identification. In ECCV.

Chen, T.; Kornblith, S.; Norouzi, M.; and Hinton, G. 2020. A simple framework for contrastive learning of visual representations. arXiv preprint arXiv:2002.05709.

Chen, Y.; Zhu, X.; and Gong, S. 2019. Instance-guided context rendering for cross-domain person re-identification. In ICCV.

Choi, Y.; Choi, M.; Kim, M.; Ha, J.-W.; Kim, S.; and Choo, J. 2018. StarGAN: Unified generative adversarial networks for multi-domain image-to-image translation. In CVPR.

Cui, S.; Wang, S.; Zhuo, J.; Li, L.; Huang, Q.; and Tian, Q. 2020. Towards discriminability and diversity: Batch nuclear-norm maximization under label insufficient situations. In CVPR.

Deng, J.; Dong, W.; Socher, R.; Li, L.-J.; Li, K.; and Fei-Fei, L. 2009. Imagenet: A large-scale hierarchical image database. In CVPR.

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

Ester, M.; Kriegel, H.-P.; Sander, J.; Xu, X.; et al. 1996. A density-based algorithm for discovering clusters in large spatial databases with noise. In KDD.

Fu, Y.; Wei, Y.; Wang, G.; Zhou, Y.; Shi, H.; and Huang, T. S. 2019. Self-similarity grouping: A simple unsupervised cross domain adaptation approach for person re-identification. In ICCV.

Ge, Y.; Chen, D.; and Li, H. 2020. Mutual mean-teaching:
Table 4: Ablation studies of our proposed approach on individual components for Duke-to-Market and Market-to-Duke adaptation tasks.

| Methods                  | Duke $\rightarrow$ Market | Market $\rightarrow$ Duke |
|--------------------------|---------------------------|---------------------------|
|                          | mAP | top-1 | top-5 | top-10 | mAP | top-1 | top-5 | top-10 |
| SSKD (w/o $L_{id}$)      | 51.3 | 74.5  | 85.7  | 89.3   | 50.2 | 67.1  | 77.4  | 80.6   |
| SSKD (w/o $L_{dt}$)      | 77.4 | 91.2  | 96.3  | 97.7   | 65.7 | 78.6  | 89.0  | 91.7   |
| SSKD (w/o $L_{BNM}$)     | 77.8 | 90.6  | 96.8  | 98.0   | 66.4 | 79.7  | 89.7  | 92.6   |
| SSKD (w/o $L_{MS}$)      | 75.9 | 89.8  | 96.2  | 97.7   | 64.0 | 79.7  | 89.7  | 92.1   |
| SSKD (w/o $\theta \cdot e$) | 46.3 | 76.0  | 86.9  | 90.5   | 42.5 | 63.5  | 76.0  | 80.0   |
| SSKD                     | 78.7 | 91.7  | 97.2  | 98.2   | 67.2 | 80.2  | 90.6  | 93.3   |

Pseudo label refinery for unsupervised domain adaptation on person re-identification.

Ghosh, A.; Kumar, H.; and Sastry, P. 2017. Robust loss functions under label noise for deep neural networks. In AAAI.

Hadsell, R.; Chopra, S.; and LeCun, Y. 2006. Dimensionality reduction by learning an invariant mapping. In CVPR.

He, K.; Fan, H.; Wu, Y.; Xie, S.; and Girshick, R. 2020. Momentum contrast for unsupervised visual representation learning. In CVPR.

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep residual learning for image recognition. In CVPR.

Hinton, G.; Vinyals, O.; and Dean, J. 2015. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531.

Hoffer, E.; and Ailon, N. 2015. Deep metric learning using triplet network. In SBPR Workshops.

Li, Y.-J.; Lin, C.-S.; Lin, Y.-B.; and Wang, Y.-C. F. 2019. Cross-dataset person re-identification via unsupervised pose disentanglement and adaptation. In ICCV.

Liu, J.; Zha, Z.-J.; Chen, D.; Hong, R.; and Wang, M. 2019. Adaptive transfer network for cross-domain person re-identification. In CVPR.

Luo, H.; Gu, Y.; Liao, X.; Lai, S.; and Jiang, W. 2019. Bag of tricks and a strong baseline for deep person re-identification. In CVPR.

Ristani, E.; Solera, F.; Zou, R.; Cucchiara, R.; and Tomasi, C. 2016. Performance measures and a data set for multi-target, multi-camera tracking. In ECCV.

Song, L.; Wang, C.; Zhang, L.; Du, B.; Zhang, Q.; Huang, C.; and Wang, X. 2018. Unsupervised domain adaptive re-identification: theory and practice. arXiv e-prints arXiv:1807.11334.

Wang, J.; Zhu, X.; Gong, S.; and Li, W. 2018. Transferable joint attribute-identity deep learning for unsupervised person re-identification. In CVPR.

Wang, X.; Han, X.; Huang, W.; Dong, D.; and Scott, M. R. 2019. Multi-similarity loss with general pair weighting for deep metric learning. In CVPR.

Wei, L.; Zhang, S.; Gao, W.; and Tian, Q. 2018. Person transfer gan to bridge domain gap for person re-identification. In CVPR.

Xu, G.; Liu, Z.; Li, X.; and Loy, C. C. 2020. Knowledge distillation meets self-supervision. arXiv preprint arXiv:2006.07114.

Yang, F.; Li, K.; Zhong, Z.; Luo, Z.; Sun, X.; Cheng, H.; Guo, X.; Huang, F.; Ji, R.; and Li, S. 2020. Asymmetric co-teaching for unsupervised cross-domain person re-identification. In AAAI.

Zhai, Y.; Lu, S.; Ye, Q.; Shan, X.; Chen, J.; Ji, R.; and Tian, Y. 2020a. Ad-cluster: Augmented discriminative clustering for domain adaptive person re-identification. In CVPR.

Zhai, Y.; Ye, Q.; Lu, S.; Jia, M.; Ji, R.; and Tian, Y. 2020b. Multiple expert brainstorming for domain adaptive person re-identification. arXiv preprint arXiv:2007.01546.

Zhang, X.; Cao, J.; Shen, C.; and You, M. 2019. Self-training with progressive augmentation for unsupervised cross-domain person re-identification. In ICCV.

Zhang, Y.; Xiang, T.; Hospedales, T. M.; and Lu, H. 2018. Deep mutual learning. In CVPR.

Zhang, Z.; and Sabuncu, M. 2018. Generalized cross entropy loss for training deep neural networks with noisy labels. In NIPS.

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

Zheng, L.; Yang, Y.; and Hauptmann, A. G. 2016. Person re-identification: Past, present and future. arXiv preprint arXiv:1610.02984.

Zhong, Z.; Zheng, L.; Kang, G.; Li, S.; and Yang, Y. 2020. Random erasing data augmentation. In AAAI.

Zhu, J.-Y.; Park, T.; Isola, P.; and Efros, A. A. 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks. In ICCV.