Exploiting Sample Uncertainty for Domain Adaptive Person Re-Identification

Kecheng Zheng\textsuperscript{1*}, Cuiling Lan\textsuperscript{2†}, Wenjun Zeng\textsuperscript{2}, Zhizheng Zhang\textsuperscript{1}, Zheng-Jun Zha\textsuperscript{1†}

\textsuperscript{1} University of Science and Technology of China
\textsuperscript{2} Microsoft Research Asia
{zkcys001,zhizheng}@mail.ustc.edu.cn, {culan, wezeng}@microsoft.com, zhazj@ustc.edu.cn

Abstract

Many unsupervised domain adaptive (UDA) person re-identification (ReID) approaches combine clustering-based pseudo-label prediction with feature fine-tuning. However, because of domain gap, the pseudo-labels are not always reliable and there are noisy/incorrect labels. This would mislead the feature representation learning and deteriorate the performance. In this paper, we propose to estimate and exploit the credibility of the assigned pseudo-label of each sample to alleviate the influence of noisy labels, by suppressing the contribution of noisy samples. We build our baseline framework using the mean teacher method together with an additional contrastive loss. We have observed that a sample with a wrong pseudo-label through clustering in general has a weaker consistency between the output of the mean teacher model and the student model. Based on this finding, we propose to exploit the uncertainty (measured by consistency levels) to evaluate the reliability of the pseudo-label of a sample and incorporate the uncertainty to re-weight its contribution within various ReID losses, including the identity (ID) classification loss per sample, the triplet loss, and the contrastive loss. Our uncertainty-guided optimization brings significant improvement and achieves the state-of-the-art performance on benchmark datasets.

1 Introduction

Person re-identification (ReID) is an important task that matches person images across times/spaces/cameras, which has many applications such as people tracking in smart retail, image retrieval for finding lost children. Existing approaches achieve remarkable performance when the training and testing data are from the same dataset/domain. But they usually fail to generalize well to other datasets where there are domain gaps (Ge, Chen, and Li\textsuperscript{2020}). To address this practical problem, unsupervised domain adaptive (UDA) person ReID attracts much attention for both the academic and industrial communities, where labeled source domain and unlabeled target domain data are exploited for training.

\textsuperscript{*}This work was done when Kecheng Zheng was an intern at MSRA.
\textsuperscript{†}Corresponding Author

Figure 1: Observations on the relations between the correctness of pseudo labels and the uncertainty (which we measure by the inconsistency level of the output features of two models, i.e., the student model and the teacher model based on the mean teacher method (Tarvainen and Valpola\textsuperscript{2017}) for the target domain samples (obtained from Duke→Market). We found the uncertainty for samples with wrong/noisy pseudo labels (red curve) is usually larger than those (green curve) with correct/clean pseudo labels.

Typical UDA person ReID approaches (Ge, Chen, and Li\textsuperscript{2020}; Zhai et al.\textsuperscript{2020a}; Zhong et al.\textsuperscript{2019}; Zheng et al.\textsuperscript{2020}; Song et al.\textsuperscript{2020}) include three steps: feature pre-training with labeled source domain data, clustering-based pseudo-label prediction for the target domain data, and feature representation learning/fine-tuning with the pseudo-labels. The last two steps are usually iteratively conducted to promote each other. However, the pseudo-labels obtained/assigned through clustering usually contain noisy (wrong) labels due to the divergence/domain gap between the source and target data, and the imperfect results of the clustering algorithm. Such noisy labels would mislead the feature learning and harm the domain adaptation performance. Thus, alleviating the negative effects of those samples with unreliable/noisy pseudo labels is important for the success of domain adaptation.
The challenge lies in 1) how to identify samples that are prone to have noisy pseudo labels; 2) how to alleviate their negative effects during the optimization. In this paper, to answer the first question, we have observed abundant samples and analyzed the relationship between the characteristics of the samples and the correctness of pseudo labels. Based on the theory on uncertainty (Kendall and Gal 2017), a model has uncertainty on its prediction of an input sample. Here, we measure the inconsistency level of the output features of two models (the student model and the teacher model) based on the mean teacher method (Tarvainen and Valpola 2017) and take it as the estimated uncertainty of a target domain sample. As shown in Fig. 1, we observe the distribution of the uncertainty (inconsistency levels) for correct/clean pseudo labels and wrong pseudo labels. We found that the uncertainty values for the samples with wrong pseudo labels are usually larger than those with correct pseudo labels. This motivates us to estimate and exploit the uncertainty of samples to alleviate the negative effects of noisy pseudo labels, enabling effective domain adaptation. We answer the second question by carefully incorporating the uncertainty of samples into classification loss, triplet loss, and contrastive loss, respectively.

We summarize our main contributions as follows:

- We propose a network named Uncertainty-guided Noise Resilient Network (UNRN) to explore the credibility of the predicted pseudo labels of target domain samples for effective domain adaptive person ReID.
- We develop an uncertainty estimation strategy by calculating the inconsistency of two models in terms of their predicted soft multilabels.
- We incorporate the uncertainty of samples to the ID classification loss, triplet loss, and contrastive loss through re-weighting to alleviate the negative influence of noisy pseudo labels.

Extensive experiments demonstrate the effectiveness of our framework and the designed components on unsupervised person ReID benchmark datasets. Our scheme achieves the state-of-the-art performance on all the benchmark datasets.

## 2 Related Work

### 2.1 Unsupervised Domain Adaptive Person ReID

Existing unsupervised domain adaptive person ReID approaches can be grouped into three main categories. **Clustering-based methods** in general generate hard or soft pseudo labels based on clustering results and then fine-tune/train the models based on the pseudo labels (Fan et al. 2018; Zhang et al. 2019; Yang et al. 2019b; Ge, Chen, and Li 2020; Yu et al. 2019; Zhong et al. 2019; Song et al. 2020; Jin et al. 2020). They are widely used due to their superior performance. PUL (Fan et al. 2018) iteratively obtains hard clustering labels and trains the model in self-training manner. SSG (Yang et al. 2019b) exploits the potential similarity for the global body and local body parts, respectively, to build multiple independent clusters. These clusters are then assigned with labels to supervise the training. PAST (Zhang et al. 2019) optimizes the network with triplet-based loss function (to capture the local structure of target-domain data points) and classification loss by appending a classification layer (to use global information about the data distribution) based on clustering results.

Pseudo label noise caused by unsupervised clustering is always an obstacle to the self-training. Such noisy labels would mislead the feature learning and impede the achievement of high performance. Recently, some methods introduce mutual learning among two/three collaborative networks to mutually exploit the refined soft pseudo labels of the peer networks as supervision (Ge, Chen, and Li 2020; Zhao et al. 2020b). To suppress the noises in the pseudo labels, NRMT (Zhao et al. 2020) maintains two networks during training to perform collaborative clustering and mutual instance selection, which reduces the fitting to noisy instances by using the mutual supervision and the reliable instance selection. These approaches need mutual learning of two or more networks and are somewhat complicated. Besides, the selection of reliable instances in NRMT (Zhao et al. 2020) is a hard rather than a soft selection, which requires a careful determination of threshold parameters and may lose the chance of exploiting useful information of the abandoned samples.

Different from the above works, in this paper, we propose a simple yet effective framework which estimates the reliability of the pseudo labels through uncertainty estimation and softly exploit them in the ReID losses to alleviate the negative effects of noise-prone samples. Note that we do not need two networks for mutual learning. We build our framework based on the mean teacher method, which maintains a temporally averaged model of the base network during the training, to facilitate the estimation of the uncertainty of each target domain sample.

**Domain translation-based methods** (Deng et al. 2018a; Huang et al. 2020b; Wei et al. 2018; Ge et al. 2020) transfer source domain labeled images to the style of the target domain images and use these transferred images and the inherited ground-truth labels to fine-tune the model. However, the quality of translated images is still not very satisfactory which hinders the advancement of these approaches.

**Memory bank based methods** have been widely used for unsupervised representation learning which facilitates the introduction of contrastive loss (He et al. 2020) for the general tasks. He et al. leverage the memory bank to better train the model to exploit the similarity between a sample and the instances in the global memory bank (He et al. 2020). Wang et al. propose to use memory bank to facilitate hard negative instance mining across batches (Wang et al. 2020). ECN (Zhong et al. 2019) leverages memory bank to enforce exemplar-invariance, camera-invariance and neighborhood-invariance over global training data (instead of local batch) for UDA person ReID. We introduce contrastive loss to the target instance memory bank to enable the joint optimization of positive pairs and negative pairs for a query/anchor sample over all the samples in the memory bank, which serves as our strong baseline.
2.2 Uncertainty Estimation

Uncertainty modeling helps us to understand what a model does not know (or is not confident). In order to suppress the noise during the training, existing works (Kendall and Gal 2017; Chang et al. 2020; Zheng and Yang 2020; Zheng, Zha, and Wei 2019) have explored uncertainty estimation from different aspects, such as the data-dependent uncertainty, model uncertainty, and the uncertainty on annotation. For fully supervised learning tasks with clean groundtruth labels, some works learn the data-dependent uncertainty in an end-to-end manner to alleviate the influence of observation noise of an input sample for better network optimization (Kendall and Gal 2017; Chang et al. 2020). Zheng et al. (Zheng and Yang 2020) use an extra auxiliary classifier to help estimate the uncertainty of the predicted pseudo labels for semantic segmentation. For clustering-based UDA person ReID, some of the pseudo labels generated by clustering are incorrect/noisy. However, the investigation on how to softly evaluate the reliability of clustering-generated pseudo labels is still underexplored. In this work, we explore the reliability estimation of the clustering-generated pseudo labels and alleviate the influence of noise-prone samples by re-weighting their contributions in ReID losses.

3 Uncertainty-guided Noise Resilient Network

Unsupervised domain adaptive person ReID aims at adapting the model trained on a labeled source domain dataset $\mathcal{D}_s = \{(x_i^s, y_i^s)\}_{i=1}^{N_s}$ of $C_s$ identities to an annotation-free target domain dataset $\mathcal{D}_t = \{x_i^t\}_{i=1}^{N_t}$. $N_s$ and $N_t$ denote the number of samples. $x_i$ denotes a sample and $y_i$ denotes its groundtruth label. Fig. 2 shows an overview of our proposed Uncertainty-guided Noise Resilient Network (UNRN) for UDA person ReID. We aim to address the negative influence of noise-prone pseudo labels during adaptation/fine-tuning under the clustering-based framework. We build a clustering-based strong baseline scheme $S_{Base}$ for UDA person ReID. On top of the strong baseline, we introduce an uncertainty calculation module to estimate the reliability of pseudo labels and incorporate the uncertainty into the ReID losses (ID classification loss (ID loss), triplet loss, and contrastive loss, respectively) to alleviate the influence of noise-prone pseudo labels. Our uncertainty-guided optimization design brings significant improvement on top of this strong baseline. We introduce the strong baseline in Section 3.1 and elaborate on our proposed uncertainty-guided noise-resilient optimization designs in Section 3.2.

3.1 Clustering-based Strong Baseline

We build a clustering-based strong baseline scheme $S_{Base}$ for UDA person ReID. We follow the general pipeline of clustering-based UDA methods (Fan et al. 2018; Song et al. 2020; Jin et al. 2020) which consists of three main stages, i.e., model pre-training, clustering, and fine-tuning.
As shown in Fig. 2, we exploit the labeled source domain data for fine-tuning, incorporate contrastive loss, and leverage the simple yet effective mean teacher method to have a strong baseline. We will present the ablation study of each component in the experimental section.

In the model pre-training stage, we pre-train the network using source domain labeled data. In the clustering stage, we do clustering on the unlabeled target domain data using the more accurate features from the mean teacher model and generate pseudo labels based on the clustering results.

**Joint fine-tuning using source data.** In the fine-tuning stage (Zhang et al., 2019), most works fine-tune the networks only using target domain pseudo labels. Here, we also reuse the valuable source domain data with reliable groundtruth labels. For a source sample, we add ID classification loss, where maintained class centers are used as the classification weight vectors for classification.

**Contrastive loss across memory bank.** For image retrieval task, to enable the pair similarity optimization over informative negative instances, Wang et al. propose a cross-batch memory mechanism that memorizes the feature embeddings of the past iterations to allow collecting sufficient hard negative pairs across the memory bank for network optimization (Wang et al., 2020). Motivated by this, for a target domain query sample $a$, we add contrastive loss to maximize the within-class similarity and minimize the between-class similarity across the memory bank. Particularly, the memory bank consists of $N$ target domain instances (which is maintained similar to (Wang et al., 2020) and $C_s$ source class center features (as the negative samples). Based on the pseudo labels of the target domain samples and the additional source class centers, we have $N^+_a$ positive samples and $N^-_a = N - N^+_a + C_s$ negative samples. We optimize their similarities with respect to the query sample. Following circle loss (Sun et al., 2020), we use self-paced weighting to softly emphasize harder sample pairs by giving larger weights to them to get effective update.

**Mean teacher method.** Mean teacher is a method that temporally averages model weights over training steps, which tends to produce a more accurate model than using the final weights directly (Tarvainen and Valpola, 2017). As illustrated in Fig. 2, there is no gradient back-propagation over the teacher model which just maintains a temporal moving average of the student model. This method is simple yet effective. We use the features from the teacher model to perform clustering and the final ReID inference.

### 3.2 Uncertainty-guided Optimization

The noisy pseudo labels would mislead the feature learning in the fine-tuning stage and hurt the adaptation performance. We aim to reduce the negative influence of noisy pseudo labels by evaluating the credibility of the pseudo label of each sample and suppress the contributions of samples with error-prone pseudo labels in the ReID losses.

**Uncertainty estimation.** Intuitively, the higher of the uncertainty the model has on its output of a sample, the lower of the reliability (larger of observation noise) of the output and it is more likely to have incorrect pseudo labels through clustering. We have observed in Fig. 1 that the samples with wrong pseudo labels in general have higher uncertainty values than those with correct pseudo labels. We leverage the uncertainty to softly assess the credibility of samples.

We estimate the uncertainty based on the output consistency between the mean teacher model and the student model. For a sample $x_t$ of the target domain, we denote the extracted feature from the student model as $f_t \in \mathbb{R}^D$ of $D$ dimensions, and the feature from the teacher model as $\tilde{f}_t \in \mathbb{R}^D$. One straightforward solution to calculate the consistency between the mean teacher model and the student model is to calculate the distance (e.g., cosine distance) between the two features. However, this is clustering ignorance which does not capture/explore the global distribution of the target domain samples.

In MAR (Yu et al., 2019), they measure the class likelihood vector (i.e., soft multilabel) of a person image with a set of reference persons (from an auxiliary domain). The inconsistency with the soft multilabel vector of an anchor sample is used to mine the hard negative sample that is visually similar to the anchor image but is of a different identity. Inspired by this, we propose to evaluate the uncertainty based on the inconsistency of the two features $f_t$ and $\tilde{f}_t$, by calculating the distance (e.g., KL distance, L1 distance) of their soft multilabels with respect to the same set of cluster centers. Particularly, as illustrated in Fig. 3, we use the class centers of source dataset and the cluster centers of the target domain data together to form the set of “reference persons”. The soft multilabel agreement is analog to the voting by the “reference persons” to evaluate the relative consistency. Besides, through the comparison with the cluster centers of the target domain data, the soft multilabel captures some global information of the clustering centers which is related to pseudo label assignment. As an auxiliary domain, the source centers provide additional references.

Let $R = [R_t, R_s] \in \mathbb{R}^{K_t \times D}$ denote a matrix which stores the features of the $K_t$ “reference persons”, with each column denoting the feature of a “reference person”. $R_t \in \mathbb{R}^{K_t \times D}$ denotes the $K_t$ cluster centers of the target do-
main data, and \( R_s \in \mathbb{R}^{K_s \times D} \) denotes the \( K_s \) class centers of the source domain data (which are obtained from the weights of the fully-connected layer of the ID classifier).

\[ K_s = K_t + K_x. \]

For a feature \( \tilde{f}_i \in \mathbb{R}^D \) from the student model, we calculate the similarity to the \( K_s \) “reference persons” and obtain the soft multilabel (likelihood vector) as:

\[ p_t = \text{Softmax} (R_t \cdot \tilde{f}_i), \]

where Softmax(\( \cdot \)) denotes softmax function which normalizes the similarity scores. Similarly, for the feature \( \tilde{f}_i \) from the mean teacher model, we obtain its soft multilabel as \( \hat{p}_t \).

We use KL divergence to measure the difference between the two probability distributions from the two models as the uncertainty \( u_i \) of the sample \( x_i \):

\[ u_i = D_{KL}(\hat{p}_i || p_i) = \sum_{k=1}^{K_s} \hat{p}_{i,k} \log \frac{\hat{p}_{i,k}}{p_{i,n}}. \]

**Optimization.** We have observed that a sample with a wrong pseudo-label (through clustering), in general, has a higher uncertainty. Based on this observation, we propose to exploit the uncertainty to estimate the unreliability of the pseudo-label of a sample and use it to re-weight the contributions of samples in various ReID losses. For a sample \( x_i \) with high uncertainty, we will reduce its contribution to the losses. Therefore, we could assign \( \omega_i = 1/u_i \) as the credibility weight. To enable more stable training, we adopt the policy in [Kendall and Gal 2017] and define \( \omega_i = \exp(-u_i) \). We incorporate the uncertainty-guided optimization in the classification loss, triplet loss, and contrastive loss, respectively.

For ID Classification loss, we define the uncertainty-guided ID classification loss in a min-batch of \( n_t \) target domain samples as

\[ \mathcal{L}_{UID} = -\frac{1}{n_t} \sum_{i=1}^{n_t} \omega_i \log p(y_i|x_i), \]

where \( p(y_i|x_i) \) denotes the probability of being class \( y_i \), where \( y_i \) denotes the pseudo groundtruth class (based on the pseudo label assigned after clustering). For a sample with high uncertainty, a smaller weight is used to reduce its contribution to the overall loss to reduce its negative effect.

As a typical sample-pair similarity optimization, triplet loss is widely used in ReID to make the similarity between an anchor sample and a positive sample to be much larger than that between this anchor sample and negative sample. For the \( j \)th triplet of an anchor sample, a positive sample and a negative sample that correspond to three pseudo labels, we approximate the reliability of a sample pair, e.g., the positive sample pair, by a function of the two uncertainties as

\[ \omega_{dp} = \varphi(u_a^j, u_p^j), \]

where \( u_a^j \) and \( u_p^j \) denote the estimated uncertainty for the anchor sample and positive sample in the \( j \)th triplet, respectively. For simplicity, we define the pair credibility as the average of two credibility as \( \omega_{ap} = \omega_a^j + \omega_p^j = \exp(-u_a^j) + \exp(-u_p^j) \). Similarly, we get \( \omega_{an} \) for the negative sample pair.

For triplet loss, we define the uncertainty-guided triplet loss in a min-batch of \( n_{tr} \) triplets as

\[ \mathcal{L}_{UTRI} = -\frac{1}{n_{tr}} \sum_{j=1}^{n_{tr}} \log \frac{\omega_{dp} \exp(s_{dp}^j)}{\omega_{dp} \exp(s_{dp}^j) + \omega_{an} \exp(s_{an}^j)}, \]

where \( s_{dp}^j \) denotes the similarity for the \( j \)th positive sample pair. Mathematically, the lower credibility (higher uncertainty) of a sample pair, the smaller of a weight on the similarity and thus a smaller gradient in optimization, i.e., contributing smaller to the optimization.

For contrastive loss, given a query/anchor sample \( x_i \), we have \( N_i^+ \) positive samples and \( N_i^- \) negative samples in the memory bank. For a batch of \( n_i \) samples, by introducing the sample pair credibility weights, the uncertainty-guided contrastive loss is as

\[ \mathcal{L}_{UCT} = \frac{1}{n_i} \sum_{k=1}^{n_i} \log \left[ 1 + \sum_{j=1}^{N_i^-} \omega_{kj} \exp(s_{kj}^i) \sum_{i=1}^{N_i^+} \omega_{ki} \exp(-s_{ki}^j) \right], \]

where \( s_{kj}^i \) denotes the similarity between the query sample \( x_i \) and the \( j \)th negative sample, and \( \omega_{kj} \) denotes the approximate reliability of the sample pair (see (4)). The lower credibility of a sample pair, the smaller the gradient and the contribution of this pair to the optimization. Note that similar to our strong baseline, we also use self-paced weighting [Sun et al. 2020] to softly emphasize harder sample pairs (whose similarity score deviates far from the optimum) by giving larger weights to them to get effective update. For simplicity, we do not present it in (6), where \( s_{kj}, s_{ki} \) denote the similarities that already re-weighted.

The total loss for the target domain data in the fine-tuning stage could be formulated as:

\[ \mathcal{L}_{target} = \mathcal{L}_{UID} + \lambda_{tr} \mathcal{L}_{UTRI} + \lambda_{ct} \mathcal{L}_{UCT} + \lambda_{reg} \mathcal{L}_{reg}, \]

where \( \mathcal{L}_{reg} = \frac{1}{n} \sum_{i=1}^{n} u_i \) is a regularization loss which prevents large uncertainty (i.e., small credibility which could reduce the first three losses) all the time. \( \lambda_{tr}, \lambda_{ct}, \) and \( \lambda_{reg} \) are weighting factors.

## 4 Experiments

### 4.1 Datasets and Evaluation Metrics

We evaluate our methods using three person ReID datasets, including DukeMTMC-reID [Duke] (Kistani et al. 2016), Market-1501 (Market) [Zheng et al. 2015] and MSMT17 (Wei et al. 2018). DukeMTMC-reID [Kistani et al. 2016] has 36,411 images, where 702 identities are used for training and 702 identities for testing. Market-1501 [Zheng et al. 2015] contains 12,936 images of 751 identities for training and 19,281 images of 750 identities for testing. MSMT17 [Wei et al. 2018] contains 126,441 images of 4,101 identities, where 1,041 identities and 3060 identities are used for training and testing respectively.

We adopt mean average precision (mAP) and CMC Rank-1/5/10 (R1/R5/R10) accuracy for evaluation.
Table 1: Performance (%) comparison with the state-of-the-art methods for UDA person ReID on the datasets of DukeMTMC-reID, Market-1501 and MSMT17. We mark the results of the second best by underline and the best results by bold text.

| Methods       | DukeMTMC→Market1501 | Market1501→DukeMTMC |
|---------------|----------------------|----------------------|
|               | mAP      | R1      | R5      | R10     | mAP      | R1      | R5      | R10     |
| ATNet (Liu et al. 2019) (CVPR’19) | 25.6    | 55.7    | 73.2    | 79.4    | 24.9    | 43.1    | 59.5    | 64.2    |
| SPPGAN+LMP (Deng et al. 2018) (CVPR’18) | 26.7    | 57.7    | 75.8    | 82.4    | 26.2    | 46.4    | 62.3    | 68.0    |
| CFSSM (Chang et al. 2019) (AAAI’19) | 28.3    | 61.2    | -       | -       | 27.3    | 49.8    | -       | -       |
| BUC (Lin et al. 2019) (AAAI’19) | 38.3    | 66.2    | 79.6    | 84.5    | 27.5    | 47.4    | 62.6    | 68.4    |
| ECN (Zhong et al. 2019) (CVPR’19) | 43.0    | 75.1    | 87.6    | 91.6    | 40.4    | 63.3    | 75.8    | 80.4    |
| UCDA (Qi et al. 2019) (ICCV’19) | 30.9    | 60.4    | -       | -       | 31.0    | 47.7    | -       | -       |
| PDA-Net (Li et al. 2019) (ICCV’19) | 47.6    | 75.2    | 86.3    | 90.2    | 45.1    | 63.2    | 77.0    | 82.5    |
| PCB-PAST (Zhang et al. 2019) (ICCV’19) | 54.6    | 78.4    | -       | -       | 54.3    | 72.4    | -       | -       |
| SSG (Yang et al. 2019b) (ICCV’19) | 58.3    | 80.0    | 90.0    | 92.4    | 53.4    | 73.0    | 80.6    | 83.2    |
| ACT (Yang et al. 2019a) (AAAI’20) | 60.6    | 80.5    | -       | -       | 54.5    | 72.4    | -       | -       |
| MPLT (Wang and Zhang 2020) (CVPR’20) | 60.4    | 84.4    | 92.8    | 95.0    | 51.4    | 72.4    | 82.9    | 85.0    |
| DAAM (Huang et al. 2020a) (AAAI’20) | 67.8    | 86.4    | -       | -       | 63.9    | 77.6    | -       | -       |
| AD-Cluster (Zhai et al. 2020a) (CVPR’20) | 68.3    | 86.7    | 94.4    | 96.5    | 54.1    | 72.6    | 82.5    | 85.5    |
| MMT (Ge, Chen, and Li 2020) (ICLR’20) | 71.2    | 87.7    | 94.9    | 96.9    | 65.1    | 78.0    | 88.8    | 92.5    |
| NRMT (Zhai et al. 2020b) (ICCV’20) | 71.7    | 87.8    | 94.6    | 96.5    | 62.2    | 77.8    | 86.9    | 89.5    |
| B-SNR+GDS-H (Hu et al. 2020) (ECCV’20) | 72.5    | 89.3    | -       | -       | 59.7    | 76.7    | -       | -       |
| MEB-Net (Zhai et al. 2020c) (ECCV’20) | 76.0    | 89.9    | 96.0    | 97.5    | 66.1    | 79.6    | 88.3    | 92.2    |
| UNRN (Ours) | 78.1    | 91.9    | 96.1    | 97.8    | 69.1    | 82.0    | 90.7    | 93.5    |

4.2 Implementation Details
We use ResNet50 pretrained on ImageNet as our backbone networks. As (Luo et al. 2019), we perform data augmentation of randomly erasing, cropping, and flipping. For source pre-training, each mini-batch contains 64 images of 4 identities. For our fine-tuning stage, when the source data is also used, each mini-batch contains 64 source-domain images of 4 identities and 64 target-domain images of 4 pseudo identities, where there are 16 images for each identity. All images are resized to 256 × 128. Similar to (Ge, Chen, and Li 2020) and (Yang et al. 2019b), we use the clustering algorithm of DBSCAN. For DBSCAN, the maximum distance between neighbors is set to $\epsilon = 0.6$ and the minimal number of neighbors for a dense point is set to 4. ADAM optimizer is adopted. The initial learning rate is set to 0.00035. We set the weighting factors $\lambda_{tri} = 1$, $\lambda_{ct} = 0.05$, and $\lambda_{reg} = 1$, where we determine them simply by making the several losses on the same order of magnitude.

4.3 Comparison with the State-of-the-arts
We compare our proposed UNRN with the state-of-the-art methods on four domain adaptation settings in Tab. 1. Our UNRN significantly outperforms the second best UDA methods by 2.1%, 3.0%, 2.4% and 2.9%, in mAP accuracy, for Duke→Market, Market→Duke, Market→MSMT, and Duke→MSMT, respectively. SSG (Yang et al. 2019b) performs multiple clustering on both global body and local body parts. DAAM (Huang et al. 2020a) introduces an attention module and incorporates domain alignment constraints. MMT (Ge, Chen, and Li 2020) uses two networks (four models) and MEB-Net (Zhai et al. 2020b) use three networks (six models) to perform mutual mean teacher training, which have high computation complexity in training. Our UNRN uses only one network (two models) in training but still significantly outperforms the best-performing MEB-Net (Zhai et al. 2020b).

4.4 Ablation Studies
Effectiveness of components in our strong baseline. We build our basic baseline Baseline following the commonly used baselines in UDA methods (Ge, Chen, and Li 2020; Song et al. 2020; Jin et al. 2020), where in the fine-tuning stage, the identity classification loss and triplet loss are used to fine-tune the network based on the pseudo labels for the target domain data. On top of Baseline, we add three components (as described in Section 3.1. Tab. 2 shows that each component brings additional significant gain and finally we have a strong baseline SBase.

Effectiveness of our uncertainty-guided optimization. We validate the effectiveness of our proposed design on top of a strong baseline SBase. In general, the stronger of a baseline, the harder one can achieve gains since the cases easy to address are mostly handled by the strong baseline. Once the new design is complementary to the strong baseline, it is valuable to advance the development of techniques.

In the strong baseline SBase., for the target domain sam-
In this paper, for clustering-based UDA person ReID, we aim to alleviate the negative influence of wrong/noisy labels during the adaptation. We have observed that a sample with a wrong pseudo-label through clustering in general has a weaker consistency between the output of the mean teacher model and the student model. Based on this finding, we propose to exploit the uncertainty (measured by consistency levels) to evaluate the reliability of the pseudo-labels. Interestingly, UNRN-R which jointly considers the target cluster centers and source centers provides the best performance. That may be because the source centers provide more references which enables the soft multilabels more informative.

**Influence of regularization loss $L_{reg}$**. The regularization loss $L_{reg}$ prevents larger uncertainty all the time. As shown in Tab.3, our final scheme UNRN-R outperforms SBase. significantly, which captures the target domain global clustering information that is helpful to estimate the reliability of pseudo labels.

**Influence of size of memory bank**. We use a queue to maintain $N$ target domain instances in the memory bank. Tab.4 shows that as the queue length $N$ increases, the performance increases but saturates when the size is around 8192.

### 5 Conclusion

In this paper, for clustering-based UDA person ReID, we aim to alleviate the negative influence of wrong/noisy labels during the adaptation. We have observed that a sample with a wrong pseudo-label through clustering in general has a weaker consistency between the output of the mean teacher model and the student model. Based on this finding, we propose to exploit the uncertainty (measured by consistency levels) to evaluate the reliability of the pseudo-label and incorporate the uncertainty to re-weight its contribution within various ReID losses, including the ID classification loss per sample, the triplet loss, and the contrastive loss. Our uncertainty-guided optimization brings significant improvement over our strong baseline and our scheme achieves the state-of-the-art performance on benchmark datasets.
6 Acknowledgments

This work was in part supported by the National Key R&D Program of China under Grant 2020AAA0105702, National Natural Science Foundation of China (NSFC) under Grants U19B2038 and 61620106009.

7 Ethical Impact

Our method is proposed to help match/identify different persons across images, which can facilitate the development of smart retail systems in the future. When the person re-ID system is used to identify the pedestrian, it may cause a violation of human privacy. Therefore, governments and officials need to carefully formulate strict regulations and laws to ensure the legal use of ReID technology and strictly protect the data.

References

Chang, J.; Lan, Z.; Cheng, C.; and Wei, Y. 2020. Data Uncertainty Learning in Face Recognition. In CVPR, 5710–5719.

Chang, X.; Yang, Y.; Xiang, T.; and Hospedales, T. M. 2019. Disjoint Label Space Transfer Learning with Common Factorised Space. In AAAI.

Deng, W.; Zheng, L.; Ye, Q.; Kang, G.; Yang, Y.; and Jiao, J. 2018a. Image-image domain adaptation with preserved self-similarity and domain-dissimilarity for person re-identification. In CVPR, 994–1003.

Deng, W.; Zheng, L.; Ye, Q.; Kang, G.; Yang, Y.; and Jiao, J. 2018b. Image-Image Domain Adaptation With Preserved Self-Similarity and Domain-Dissimilarity for Person Re-Identification. In CVPR.

Fan, H.; Zheng, L.; Yan, C.; and Yang, Y. 2018. Unsupervised person re-identification: Clustering and fine-tuning. TOMM 14(4): 1–18.

Ge, Y.; Chen, D.; and Li, H. 2020. Mutual Mean-Teaching: Pseudo Label Refinery for Unsupervised Domain Adaptation on Person Re-identification. In ICLR.

Ge, Y.; Zhu, F.; Zhao, R.; and Li, H. 2020. Structured domain adaptation for unsupervised person re-identification. arXiv preprint arXiv:2003.06650.

He, K.; Fan, H.; Wu, Y.; Xie, S.; and Girshick, R. 2020. Momentum contrast for unsupervised visual representation learning. In CVPR, 9729–9738.

Huang, Y.; Peng, P.; Yi Jin, Y. L.; Xing, J.; and Ge, S. 2020a. Domain Adaptive Attention Model for Unsupervised Cross-Domain Person Re-Identification. In AAAI.

Huang, Y.; Zha, Z.-J.; Fu, X.; Hong, R.; and Li, L. 2020b. Real-world Person Re-Identification via Degradation Invariance Learning. In CVPR, 14084–14094.

Jin, X.; Lan, C.; Zeng, W.; and Chen, Z. 2020. Global Distance-distributions Separation for Unsupervised Person Re-identification. In ECCV.

Kendall, A.; and Gal, Y. 2017. What uncertainties do we need in bayesian deep learning for computer vision? In NeurIPS, 5574–5584.

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.

Lin, Y.; Dong, X.; Zheng, L.; Yan, Y.; and Yang, Y. 2019. A Bottom-Up Clustering Approach to Unsupervised Person Re-identification. In AAAI.

Liu, J.; Zha, Z.; 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 CVPRW.

Qi, L.; Wang, L.; Hui, J.; Zhou, L.; Shi, Y.; and Gao, Y. 2019. A Novel Unsupervised Camera-aware Domain Adaptation Framework for Person Re-identification. In ICCV.

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 ECCVW, 17–35.

Song, L.; Wang, C.; Zhang, L.; Du, B.; Zhang, Q.; Huang, C.; and Wang, X. 2020. Unsupervised domain adaptive re-identification: Theory and practice. Pattern Recognition 107173.

Sun, Y.; Cheng, C.; Zhang, Y.; Zhang, C.; Zheng, L.; Wang, Z.; and Wei, Y. 2020. Circle Loss: A Unified Perspective of Pair Similarity Optimization. In CVPR.

Tarvainen, A.; and Valpola, H. 2017. Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results. In NeurIPS, 1195–1204.

Wang, D.; and Zhang, S. 2020. Unsupervised Person Re-identification via Multi-label Classification. In CVPR.

Wang, X.; Zhang, H.; Huang, W.; and Scott, M. R. 2020. Cross-Batch Memory for Embedding Learning. In CVPR, 6388–6397.

Wei, L.; Zhang, S.; Gao, W.; and Tian, Q. 2018. Person transfer GAN to bridge domain gap for person re-identification. In CVPR, 79–88.

Yang, F.; Li, K.; Zhong, Z.; Luo, Z.; Sun, X.; Cheng, H.; Guo, X.; Huang, F.; Ji, R.; and Li, S. 2019a. Asymmetric Co-Teaching for Unsupervised Cross Domain Person Re-identification. In AAAI.

Yang, F.; Yunchao, W.; Guanshuo, W.; Yuqian, Z.; Honghui, S.; and Thomas, H. 2019b. Self-similarity Grouping: A Simple Unsupervised Cross Domain Adaptation Approach for Person Re-identification. In ICCV.

Yu, H.-X.; Zheng, W.-S.; Wu, A.; Guo, X.; Gong, S.; and Lai, J.-H. 2019. Unsupervised Person Re-identification by Soft Multilabel Learning. In CVPR.

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.; Lv, S.; Ye, Q.; Chen, J.; Ji, R.; and Tian, Y. 2020b. 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. 2020c. Multiple expert brainstorming for domain adaptive person re-identification. In ECCV.

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

Zhao, F.; Liao, S.; Xie, G.-S.; Zhao, J.; Zhang, K.; and Shao, L. 2020. Unsupervised domain adaptation with noise resistible mutual-training for person re-identification. In ECCV.

Zheng, K.; Liu, W.; Liu, J.; Zha, Z.; and Mei, T. 2020. Hierarchical Gumbel Attention Network for Text-based Person Search. In ACMMM.

Zheng, K.; Zha, Z.-J.; and Wei, W. 2019. Abstract reasoning with distracting features. In NeurIPS, 5842–5853.

Zheng, L.; Shen, L.; Tian, L.; Wang, S.; Wang, J.; and Tian, Q. 2015. Scalable person re-identification: A benchmark. In ICCV, 1116–1124.

Zheng, Z.; and Yang, Y. 2020. Rectifying Pseudo Label Learning via Uncertainty Estimation for Domain Adaptive Semantic Segmentation. arXiv preprint arXiv:2003.03773 .

Zhong, Z.; Zheng, L.; Luo, Z.; Li, S.; and Yang, Y. 2019. Invariance matters: Exemplar memory for domain adaptive person re-identification. In CVPR.