Hard-sample Guided Hybrid Contrast Learning for Unsupervised Person Re-Identification

Zheng Hu1, Chuang Zhu1,*, Gang He1
1Beijing Laboratory of Advanced Information Networks
Beijing Key Laboratory of Network System Architecture and Convergence
Beijing University of Posts and Telecommunications
Beijing 100876, China
{huzheng95, czhu, brianhe}@bupt.edu.cn

Abstract

Unsupervised person re-identification (Re-ID) is a promising and very challenging research problem in computer vision. Learning robust and discriminative features with unlabeled data is of central importance to Re-ID. Recently, more attention has been paid to unsupervised Re-ID algorithms based on clustered pseudo-label. However, the previous approaches did not fully exploit information of hard samples, simply using cluster centroid or all instances for contrastive learning. In this paper, we propose a Hard-sample Guided Hybrid Contrast Learning (HHCL) approach combining cluster-level loss with instance-level loss for unsupervised person Re-ID. Our approach applies cluster centroid contrastive loss to ensure that the network is updated in a more stable way. Meanwhile, introduction of a hard instance contrastive loss further mines the discriminative information. Extensive experiments on two popular large-scale Re-ID benchmarks demonstrate that our HHCL outperforms previous state-of-the-art methods and significantly improves the performance of unsupervised person Re-ID. The code of our work and dataset are available soon at https://github.com/bupt-ai-cz/HHCL-ReID.

Keywords: Unsupervised Learning; Person Re-ID; Hard Sample; Contrastive Learning, Pseudo Label.

1. Introduction

Person Re-ID aims to identify the same person under different cameras views. It has been used extensively in large-scale surveillance systems. Though great progress has been made in supervised person Re-ID tasks, the reliance on extensive manual annotation greatly constrains its application.

Nevertheless, collecting pedestrian images without annotation is much cheaper and easier. Thus, increasing research attention has been drawn to unsupervised person Re-ID, directly learning from unlabeled data, which is more scalable and has more potential to deployments in the real world.

The extant unsupervised person re-ID methods can be broadly divided into two categories, unsupervised domain adaptation Re-ID methods and purely unsupervised Re-ID methods. The first type methods are based on unsupervised domain adaption (UDA) where the source domain dataset is fully annotated and the target domain is an unlabeled dataset. Most of these UDA-based methods address this task by learning the knowledge in the labeled source domain dataset and transferring them to the unlabeled target domain dataset [32] [1] [8]. The second type of unsupervised Re-ID method is pseudo-label-based fully unsuper-

Figure 1. Hard-sample guided hybrid contrast learning. According to the features saved in the memory bank, we calculate cluster-level contrastive loss and hard instance-level contrastive loss, respectively. (a) Cluster centroid leads the optimization trend of features, resulting in features belonging to the same cluster being more compact and strengthen identity similarity. (b) Hard instance contrastive loss compares input sample with hard positive that belong to the same cluster and hard negative instances from other clusters, thereby learning to distinguish easily confusing samples. (Best viewed in color)
vised learning that directly learn from unlabeled data in the target domain and use representation features to estimate pseudo labels \[23, 29, 9\]. This method does not require any annotations and is more challenging. Existing fully unsupervised Re-ID works mainly aim to exploit pseudo labels from clustering and apply contrastive learning which has shown excellent performance in unsupervised representation learning \[27, 3, 11\].

The performance of the unsupervised methods relies on feature representation learning. More recently, the State-of-the-art method \[11\] using a memory bank unit \[28\] to store all instance features, treats each image as an individual class, and learns the representation by matching features of the same instance in different augmented views. However, each class usually contains more than one positive instance in Re-ID datasets. SpCL \[9\] method alleviates this problem by matching an instance with the centroid of the multiple positives. To further ensure each positive converges to its centroid at a uniform pace, cluster contrast learning \[4\] updates the memory dictionary and computes contrastive loss in the cluster level.

Although cluster contrast learning \[4\] has achieved impressive performance, the method of applying contrastive learning only in the cluster level does not consider the relationship between hard instances in the instance level. In fact, previous works in deep metric learning have focused on hard sample mining to lay more emphasis on hard samples inside a class. These methods aim to distinguish samples from different categories and bring samples from the same category closer together. However, these methods usually adopt a mini-batch-based deep metric loss, such as hard triplet loss \[13\] and multi-similarity loss \[25\]. Meanwhile, these losses only utilized a small portion of data without considering the information of all categories.

To learn discriminative feature representation for Re-ID and address the lack of adequately exploring information of hard samples, this paper introduces a novel hard-sample mining strategy and proposes a simple and effective method of hard-sample guided hybrid contrast learning for unsupervised Re-ID. In summary, this paper makes the following contributions:

- We propose a hybrid contrast learning framework for unsupervised person Re-ID which combines both cluster-level contrastive loss and instance-level contrastive loss.
- We introduce a novel hard instance mining strategy, which is based on an instance memory bank, to explore more discriminative information by selecting global hard samples online for each input instance.
- Extensive experiments on two popular large-scale Re-ID benchmarks demonstrate that our HHCL outperforms previous state-of-the-art methods and significantly improves the performance of unsupervised person Re-ID.

2. Related Works

2.1. Unsupervised Re-ID

The domain adaptation strategy has been widely used for unsupervised person Re-ID tasks \[11, 8\]. The transfer-based methods follow the strategy of UDA, which uses the pretrained model in the labeled source domain dataset as the initialization of the target domain, or uses the style transfer method to transfer labeled images to the target domain. However, the UDA approach can be very challenging when the categories in the two domains are quite different. The drawback with pseudo-labels is that if the domains are not similar enough, it is not easy for us to obtain high quality pseudo labels, because the labeling noise might be too high to hurt the performance.

More recently, researchers have given more attention to pseudo-label-based methods that do not require source domain data. The pseudo labels can be generated by a pretrained classifier or by a feature similarity-based clustering algorithm, such as K-means, DB-SCAN \[6\]. In this way, the pseudo labels are applied to fine-tuning the Re-ID model in a supervised manner. HCT \[11\] combined hierarchical clustering with hard-batch triplet loss to improve the quality of pseudo labels. MMCL \[22\] formulated unsupervised person re-ID as a multi-label classification task to progressively seek true labels. SpCL \[9\] adopted the self-paced contrastive learning strategy to form more reliable clusters. CAACL \[16\] designed an asymmetric contrastive learning framework to help the siamese network effectively mine the invariance in feature learning.

2.2. Mining Schemes

Sampling is a fundamental operation for reducing bias during model learning. Random sampling is one of the commonly used approaches, and different sampling methods are proposed to facilitate the learning of various loss functions. For the person re-ID task, identity sampling is widely used during the training stage, such as pair-wise sampling for contrastive loss and semi-hard negative mining method for triplet loss.

Hard sample mining is considered as a vital component of many deep metric learning algorithms \[28\] to accelerate network convergence or to improve the final discriminative ability of the neural network because hard samples are more informative for training. The training should focus more on hard samples than easy samples. However, existing hard mining schemes of deep metric learning based on mini-batch training data often suffer from slow convergence, because they employ only one negative or partial
negative example in mini-batch while not interacting with the other negative classes that have not been sampled into the current mini-batch in each update. In this paper, we propose a new strategy selecting the global hard samples from a memory bank for each input feature, to improve the model performance. Our hard mining strategy considers the relationship between each query instance and other clusters of different pseudo labels rather than taking into account only the inter-instance relationship with a small fraction of the categories.

3. Preliminaries

Given an unlabeled training set \( \mathcal{X} = \{x_1, x_2, ..., x_n\} \) consisting of \( n \) image samples, the goal is to learn \( \phi(\cdot; \theta) \)—an encoder parameterized by \( \theta \) used to extract features from input images. For inference, this encoder is applied to the gallery set \( \mathcal{X}^g = \{x^g_1, x^g_2, ..., x^g_h\} \) and query set \( \mathcal{X}^q = \{x^q_1, x^q_2, ..., x^q_n\} \). The gallery set contains the total collection of retrieval images in the database and representations of the query images \( \phi(x^q_i; \theta) \) are used to search the gallery set to retrieve the most similar matches to \( x^q_i \) according to Euclidean distance between the query and gallery embeddings, \( d(x^q, x^g) = ||\phi(x^q; \theta) - \phi(x^g; \theta)|| \), where a smaller distance implies increased similarity between the images. Thus, feature representations of the same person are supposed to be as close as possible.

4. Method

4.1. Architecture

Our hybrid contrast learning framework for fully unsupervised Re-ID consists of two main components: Cluster Centroid Contrastive Loss (CCCL) and Hard Instance Contrastive Loss (HICL). As shown in Fig. 2.

4.2. Hybrid Contrast Learning

To increase intra-class compactness and inter-class separability, state-of-the-art contrastive learning methods minimize the distance between samples of the same category and maximize the distance between samples of different categories with InfoNCE loss [21].

\[
\mathcal{L}_q = \mathbb{E}[-\log \frac{\exp(q \cdot k^+)}{\sum_{k=1}^{K} \exp(q \cdot k^+)}],
\]

where \( q \) is an encoded query and \( k^+ \) is a positive feature which has the same label with \( q \) selected from a set of candidates \( k^1, k^2, ..., k^K \). \( \tau \) is a temperature hyper-parameter that controls the scale of similarities.

Comparing the non-parametric loss functions of different approaches based on the memory dictionary, the SSL [17] considers each image as an individual instance and computes the loss and updates the memory dictionary both in the instance level so that all features of the training data need to be saved. To decrease memory usage and take full advantage of clustering outliers, SPCL [9] computes the loss in cluster level but updates the memory dictionary in the instance level. However, the updating progress for each cluster is inconsistent due to the varying cluster size and randomness of sampling. ClusterNCE loss [4] updates the feature vectors and computes the loss both in the cluster level. Although only a smaller storage space needs to be created to hold a cluster size amount of features for ClusterNCE, a single feature vector is not enough for a cluster representation. The averaged momentum representations calculated from all instances belonging to one cluster may lose the intra-class diversity. If updating cluster representation with only an instance feature, would introduce more biases because of noisy pseudo labels generated by unsupervised clustering.

Thus, we proposed a new unsupervised Re-ID framework that combines cluster-level loss with instance-level loss. The overall loss function of our method is as follow:

\[
\mathcal{L}_{ReID} = \mu \mathcal{L}_{cls} + (1 - \mu) \mathcal{L}_{ins},
\]

where \( \mu \) is a balancing factor and we set \( \mu = 0.5 \) by default. In the following, we will detail the objective function Eq. 1.

**Cluster Centroid Contrastive Loss** Some instance-level memory dictionary techniques, such as [22] [8] maintaining each instance feature of the dataset and update corresponding memory dictionary with its own instance features in each mini-batch, have the problem of memory updating consistency [4]. Since different instances within the same cluster will have different updating states. In every training iteration, due to the unbalanced distribution of cluster size, a smaller cluster could have a higher proportion of instances updated than a larger cluster. Unlike the previous instance-level memory dictionary, we use cluster-level memory dictionary \( \mathcal{M}_{cls} \) to keep one cluster feature for each cluster instead of preserving every instance feature. The corresponding memory dictionary is updated regardless of whether the clusters are large or small, ensuring updating consistency of features within the same cluster.

\[
\mathcal{L}_{cls} = \mathbb{E}[-\log \frac{\exp(q \cdot c^+)}{\sum_{i=1}^{C} \exp(q \cdot c^i)}/\tau_e],
\]

where \( C \) is the number of clusters in a training epoch and \( \tau_e \) is a temperature hyper-parameter. Different from unified contrastive loss, outliers are dropped out.

We calculate cluster centroids \( c^1, c^2, ..., c^C \) and store them in a memory for the cluster centroid contrastive loss. We update the cluster memory bank as follows:

\[
c^i \leftarrow \alpha c^i + (1 - \alpha) \bar{c}^i,
\]

where \( \bar{c}^i \) is the average of \( i \)-th class instance features in the mini-batch.
Figure 2. Hybrid Contrast Learning Framework. 1) Initialization: clustering algorithm divides all features extracted from the training set into different clusters as pseudo labels and initialize instance memory bank and cluster centroid memory bank; 2) forward propagate: calculate cluster contrastive loss between the input and the clustering centroids and the hard instance contrastive loss of the hard samples selected by hard mining strategy respectively; 3) back propagate and update the encoder model; 4) update instance memory bank and cluster centroid memory bank.

4.3. Memory Based Hard Mining Scheme

To further distinguish easily confused sample pairs and explore the inter-instance relationship, we propose a novel hard sample mining strategy based on a memory dictionary. We construct another memory-based dictionary $M_{ins}$ to store $P \times C$ instance features, which contains $C$ pseudo identities and each identity has $P$ instances. As shown in Fig[1], unlike traditional hard mining strategies such as hard triplet loss [13], which is based on pairwise loss calculating the distance of the hardest positive and the hardest negative instances within a mini-batch, our proposed method is based on all pseudo-labeled categories and contains $C - 1$ negative samples for each query. Our hard mining strategy considers the relationship between each query instance and other clusters of different pseudo labels rather than taking into account only the inter-instance relationship with a small fraction of the categories.

For the same query, we construct $C$ sample pairs which include one positive pair and $C - 1$ hard negative pairs. We define hard instance contrastive loss as follows:

$$L_{ins} = \mathbb{E}[- \log \frac{\exp(<q \cdot z^+_{\text{hard}}>) / \tau_{ins}}{\sum_{i=1}^C \exp(<q \cdot z^i_{\text{hard}}>) / \tau_{ins}}]$$

(5)

where $\tau_{ins}$ is an instance temperature hyper-parameter, $z^+_{\text{hard}}$ is the hard positive instance feature that has the lowest cosine similarity with query $q$ within the same cluster, and $z^i_{\text{hard}}$ is hard negative instance feature that has the highest cosine similarity that belongs to $i$-th class. They are respectively defined as

$$z^+_{\text{hard}} = \arg\min_k(<q \cdot z_k^+>)$$

$$z^i_{\text{hard}} = \arg\max_k(<q \cdot z_k^i>)$$

(6)

(7)

Similarly, to ensure memory updating consistency, all instance features of the corresponding K identities in the mini-batch are updated in each training iteration. We update the instance memory bank as follows:

$$m_k \leftarrow z_k^i.$$  

(8)

5. Experiments

5.1. Data and Metrics

We evaluate our approach on two large-scale benchmark datasets: Market1501 [33], and DukeMTMC-reID [35] which are widely used real-world person Re-ID tasks.

Market1501 contains 1,501 person identities with 32,668 images which are captured by 6 cameras in front of the Tsinghua University campus. It contains 12,936 images of 751 identities for training and 19,732 images of 750 identities for testing. All of the images were cropped by a pedestrian detector which inevitably introduced little misalignment, part missing and false positives.
DukeMTMC-reID consists a total of 36,411 images of people from 1404 different identities collected by 8 cameras. Specifically, The dataset is split by randomly selecting 702 identities as the training set and 702 identities as the testing set. It contains 16,522 images for training, 2,228 query images and 17,661 gallery images for testing.

**Evaluation Metrics.** We followed the standard training/test split and evaluation protocol to evaluate the performance of our method. For the evaluation metrics, we used the Rank-k (for k = 1, 5, and 10) matching accuracy, which means the query picture has the match in the top-k list. And we use the mean Average Precision (mAP), which is computed from the Cumulated Matching Characteristics (CMC) \(10\). Moreover, results reported in this paper are under the single-query setting, and no post-processing technique is applied.

### 5.2. Implementation

We adopt ResNet-50 \([12]\) as the backbone of the feature extractor and initialize the model with the parameters pre-trained on ImageNet \([5]\). After layer-4, we remove all sub-module layers and add global average pooling (GAP) followed by batch normalization layer \([14]\) and L2-normalization layer, which will produce 2048-dimensional features. During testing, we take the features of the global average pooling layer to calculate the distance. For the beginning of each epoch, we use DB-SCAN \([6]\) for clustering to generate pseudo labels. The input image is resized 256 x 128. For training images, we perform random horizontal flipping, padding with 10 pixels, random cropping, and random erasing. Each mini-batch contains 256 images of 16 pseudo person identities (16 instances for each person). We adopt Adam optimizer to train the Re-ID model with weight decay 5e-4. The initial learning rate is set to 3.5e-4, and is reduced to 1/10 of its previous value every 20 epoch in a total of 50 epoch. As the same with the cluster method of \([9]\) paper, we use DB-SCAN and Jaccard distance \([50]\) to cluster with k nearest neighbors, where k = 30. For DB-SCAN, the maximum distance d between two samples is set as 0.45 and the minimal number of neighbors in a core point is set as 4.

### 5.3. Results

#### 5.3.1 Comparison with unsupervised method

We compare our proposed method with state-of-the-art ReID methods including: 1) the unsupervised domain adaptation methods for person Re-ID (e.g. ECN \([37]\), MAR \([37]\), SSG \([7]\), MMCL \([22]\), JVTC \([15]\), DG-Net++ \([40]\), ECN++ \([38]\), MMT \([8]\), DCML \([1]\), MEB \([32]\), SpCL \([9]\); 2) the purely unsupervised methods for person Re-ID SSL \([9]\), MMCL \([22]\), JVTC \([15]\), HCT \([31]\), CycAs \([26]\), SpCL \([9]\), CAP \([24]\), CACL \([16]\), CCL \([4]\) and ICE \([2]\). The comparison results of the state-of-the-art unsupervised domain adaptation methods and purely unsupervised methods on Market-1501 and DukeMTMC-reID are reported in Tab.1.

As shown in Tab.1, we observe our method is competitive with all the state-of-the-art methods. On the three datasets, our proposed HHCL without any identity annotation achieves better performance than all of UDA methods that use of the additional labeled source dataset. It can be found that we not only perform better than all unsupervised domain adaptation methods and also achieve competitive performance with purely unsupervised methods. Under the fully unsupervised setting, HHCL achieves 84.2% in mAP and 93.4% in rank-1 accuracy on Market-1501, which is 1.9% higher than the current state of the art (ICE \([4]\)). On DukeMTMC-reID, our method also achieves a high performance of 73.3/85.1% in mAP/rank-1. These results indicate that our method is effective for unsupervised person Re-ID learning.

#### 5.3.2 Comparison with supervised method

Our HHCL method can be easily implemented as a supervised approach when we replace the pseudo-labels with ground truth. We further find that our proposed unsupervised method is already comparable to some excellent supervised methods.
Table 1. Experimental results of the proposed HHCL and state-of-the-art methods on Market-1501 and DukeMTMC-reID. Note that the best results are bolded.

| Method            | Reference | Unsupervised Domain Adaptation | Fully Unsupervised | Supervised |
|-------------------|-----------|--------------------------------|--------------------|------------|
|                   |           | Market1501                      | DukeMTMC-reID      |
|                   |           | mAP R1 R5 R10                   | mAP R1 R5 R10      |
| ECN [37]          | CVPR’19   | 43.0 75.1 87.6 91.6             | 40.4 63.3 75.8 80.4 |
| MAR [30]          | CVPR’19   | 40.0 67.7 81.9 -                | 48.0 67.1 79.8 -   |
| SSG [7]           | ICCV’19   | 58.3 80.0 90.0 92.4             | 53.4 73.0 80.6 83.2 |
| MMCL [22]         | CVPR’20   | 60.4 84.4 92.8 95.0             | 51.4 72.4 82.9 85.0 |
| JVT [15]          | ECCV’20   | 61.1 83.8 93.0 95.2             | 56.2 75.0 85.1 88.2 |
| DG-Net++[40]      | ECCV’20   | 61.7 82.1 90.2 92.7             | 63.8 78.9 87.8 90.4 |
| ECN+ [38]         | PAMI’20   | 63.8 84.1 92.8 95.4             | 54.4 74.0 83.7 87.4 |
| MMT [8]           | ICLR’20   | 71.2 87.7 94.9 96.9             | 65.1 78.0 88.8 92.5 |
| DCM [11]          | ECCV’20   | 72.6 87.9 95.0 96.7             | 63.3 79.1 87.2 89.4 |
| MEB [22]          | ECCV’20   | 76.0 89.9 96.0 97.5             | 66.1 79.6 88.3 92.2 |
| SpCL [9]          | NeurIPS’20| 76.7 90.3 96.2 97.7             | 68.8 82.9 90.1 92.5 |
| SSL [17]          | CVPR’20   | 37.8 71.7 83.8 87.4             | 28.6 52.5 63.5 68.9 |
| JVT [15]          | ECCV’20   | 41.8 72.9 84.2 88.7             | 42.2 67.6 78.0 81.6 |
| MMCL [22]         | CVPR’20   | 45.5 80.3 89.4 92.3             | 40.2 65.2 75.9 80.0 |
| HCT [31]          | CVPR’20   | 56.4 80.0 91.6 95.2             | 50.7 69.6 83.4 87.4 |
| CycAs [26]        | ECCV’20   | 64.8 84.8 - -                   | 60.1 77.9 - -      |
| SpCL [9]          | NeurIPS’20| 73.1 88.1 95.1 97.0             | 65.3 81.2 90.3 92.2 |
| CAP [21]          | AAAI’21   | 79.2 91.4 96.3 97.7             | 67.3 81.1 89.3 91.8 |
| CAACL [16]        | Arxiv’21  | 80.9 92.7 97.4 98.5             | 69.6 82.6 91.2 93.8 |
| ICE [2]           | ICCV’21   | 82.3 93.8 97.6 98.4             | 69.9 83.3 91.5 94.1 |
| CCL [4]           | Arxiv’21  | 82.6 93.0 97.0 98.1             | 72.8 85.7 92.0 93.5 |
| HHCL              | This paper| 84.2 93.4 97.7 98.5             | 73.3 85.1 92.4 94.6 |

Table 2. Evaluation of parameter $\mu$ on Market1501.

| $\mu$ | Market1501 |
|-------|------------|
|       | mAP R1 R5 R10 |
| 0(hard)| 78.5 90.5 96.0 97.4 |
| 0.25  | 85.6 93.9 98.8 99.1 |
| 0.5   | 84.2 93.4 97.7 98.5 |
| 0.75  | 80.8 91.3 96.3 97.6 |

5.4. Ablation Study

**Influence of Hyper-Parameter $\mu$** Tab. 2 reports the experiment result under different value of hyper-parameter $\mu$. As mentioned in $\mu$ is a balancing factor between 0 and 1, which plays an important role in affecting the weights of the cluster-level loss and instance-level loss. When $\mu$ is equal to 0, the loss function contains only the hard instance contrastive loss. From the fig. 3, we can find that the model converges very slowly in the early stage of the training process, and using only the hard samples for comparison is not benefit for learning generalized features and obtaining better clustering pseudo labels. On the contrary, when $\mu=1$ and cluster-level loss only is used, although a faster convergence can be achieved, only one feature is retained for each cluster, which loses the diversity of intra class and is still not conducive to facilitating the network to learn more discriminative features. It can be seen that combining both kind supervised methods, such as PCB [20] and DG-Net [34], when ground truth is not used. And our HHCL even achieves a better performance under supervised setting. This result shows that our proposed method achieves better results when using the ground truth to avoid introducing noisy pseudo-lables. And it also further demonstrates the effectiveness of our method for the person Re-ID problem, both unsupervised and supervised.
of contrastive loss leads to better performance obviously. And when \( \mu = 0.5 \), we get the best performance 84.2\% in mAP, indicating that our proposed hybrid contrastive learning method has a distinct advantage over others during the training process.

![Figure 3. Ablation study on Market1501: Result comparisons of different settings in mAP and Rank-1.](image)

| Method     | Market1501 | DukeMTMC-reID |
|------------|------------|---------------|
|            | mAP | R1 | R5 | R10 | mAP | R1 | R5 | R10 |
| ResNet50   | 84.2 | 93.4 | 97.7 | 98.5 | 73.3 | 85.1 | 92.4 | 94.6 |
| IBN + GeM  | 87.8 | 95.1 | 98.2 | 98.8 | 76.8 | 87.9 | 93.4 | 94.9 |
| IBN + GeM + LS | 88.2 | 94.9 | 98.3 | 98.9 | 77.3 | 87.7 | 93.5 | 95.1 |

Table 3. Comparison of HHCL with other tricks on Market1501 and DukeMTMC-reID datasets. 'IBN' denotes that the backbone applies IBN-ResNet50. 'GeM' and 'LS' represent GeM pooling layer and label smoothing respectively.

![Figure 6. Ablation study on Market1501: Result comparisons of different settings in mAP and Rank-1.](image)

In this paper, we propose a novel method for the fully unsupervised person re-ID. The new concepts and techniques introduced include a more efficient hybrid contrast learning framework and a memory based hard sample mining scheme. Specifically, our proposed HHCL approach comprehensively consider both of cluster level and instance level information. For effectively exploiting the invariance within and between clusters, HHCL leverages hard samples to guide network to learn more robust and discriminative features. Extensive experiments on two benchmark datasets demonstrated that HHCL achieves the best results comparing with all existing purely unsupervised and UDA-based Re-ID methods.

### Acknowledgements

This work was supported in part by 111 Project of China (B17007), and in part by the National Natural Science Foundation of China (61602011).

### References

[1] Guangyi Chen, Yuhao Lu, Jiwen Lu, and Jie Zhou. Deep credible metric learning for unsupervised domain adaptation person re-identification. In ECCV, 2020.

[2] Hao Chen, Benoit Lagadec, and F. Brémond. Ice: Inter-instance contrastive encoding for unsupervised person re-identification. ArXiv, abs/2103.16364, 2021.

[3] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey E. Hinton. A simple framework for contrastive learning of visual representations. ArXiv, abs/2002.05709, 2020.

[4] Zuozhuo Dai, Guangyuan Wang, Siyu Zhu, Weihao Yuan, and P. Tan. Cluster contrast for unsupervised person re-identification. ArXiv, abs/2103.11568, 2021.

[5] Jia Deng, Wei Dong, R. Socher, Li-Jia Li, K. Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In CVPR, 2009.

[6] Martin Ester, H. Kriegel, J. Sander, and Xiaowei Xu. A density-based algorithm for discovering clusters in large spatial databases with noise. In KDD, 1996.

[7] Yang Fu, Yunchao Wei, Guanshuo Wang, Xi Zhou, Humphrey Shi, and Thomas S. Huang. Self-similarity grouping: A simple unsupervised cross domain adaptation approach for person re-identification. 2019 IEEE/CVF International Conference on Computer Vision (ICCV), pages 6111–6120, 2019.

[8] Yixiao Ge, Dapeng Chen, and Hongsheng Li. Mutual mean-teaching: Pseudo label refinery for unsupervised domain adaptation on person re-identification. ArXiv, abs/2001.01526, 2020.
[9] Yixiao Ge, Dapeng Chen, Feng Zhu, Rui Zhao, and Hongsheng Li. Self-paced contrastive learning with hybrid memory for domain adaptive object re-id. ArXiv, abs/2006.02713, 2020.

[10] Douglas Gray, Shane Brennan, and Hai Tao. Evaluating appearance models for recognition, reacquisition, and tracking. 2007.

[11] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross B. Girshick. Momentum contrast for unsupervised visual representation learning. 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 9726–9735, 2020.

[12] Kaiming He, X. Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 770–778, 2016.

[13] Alexander Hermans, L. Beyer, and B. Leibe. In defense of the triplet loss for person re-identification. ArXiv, abs/1703.07737, 2017.

[14] S. Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. ArXiv, abs/1502.03167, 2015.

[15] Jianing Li and Shiliang Zhang. Joint visual and temporal consistency for unsupervised domain adaptive person re-identification. In ECCV, 2020.

[16] Mingkun Li, Chun-Guang Li, and Jun Guo. Cluster-guided asymmetric contrastive learning for unsupervised person re-identification. ArXiv, abs/2106.07846, 2021.

[17] Yutian Lin, Lingxi Xie, Yu Wu, C. Yan, and Qi Tian. Unsupervised person re-identification via softened similarity learning. 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 3387–3396, 2020.

[18] Xingang Pan, Ping Luo, Jianping Shi, and Xiaoou Tang. Two at once: Enhancing learning and generalization capacities via ibn-net. In ECCV, 2018.

[19] Filip Radenović, Giorgos Tolias, and O. Chum. Fine-tuning cnn image retrieval with no human annotation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 41:1655–1668, 2019.

[20] Yifan Sun, L. Zheng, Y. Yang, Q. Tian, and S. Wang. Beyond part models: Person retrieval with refined part pooling. In ECCV, 2018.

[21] Airon van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. ArXiv, abs/1807.03748, 2018.

[22] Dongkai Wang and Shiliang Zhang. Unsupervised person re-identification via multi-label classification. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10981–10990, 2020.

[23] Hanxiao Wang, Xiatian Zhu, T. Xiang, and S. Gong. Towards unsupervised open-set person re-identification. 2016 IEEE International Conference on Image Processing (ICIP), pages 769–773, 2016.

[24] Menglin Wang, B. Lai, Jianqiang Huang, Xiaojin Gong, and Xiansheng Hua. Camera-aware proxies for unsupervised person re-identification. In AAAI, 2021.

[25] Xun Wang, Xintong Han, Weilin Huang, Dengke Dong, and M. Scott. Multi-similarity loss with general pair weighting for deep metric learning. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 5017–5025, 2019.

[26] Zhongdao Wang, Jingwei Zhang, Liang Zheng, Yixuan Liu, Yifan Sun, Yali Li, and Shengjin Wang. Cycas: Self-supervised cycle association for learning re-identifiable descriptions. In Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020. Proceedings, Part XI 16, pages 72–88. Springer, 2020.

[27] Zhirong Wu, Yuanjun Xiong, Stella X. Yu, and Dahua Lin. Unsupervised feature learning via non-parametric instance discrimination. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 3733–3742, 2018.

[28] Zhirong Wu, Yuanjun Xiong, Stella X. Yu, and Dahua Lin. Unsupervised feature learning via non-parametric instance-level discrimination. ArXiv, abs/1805.01978, 2018.

[29] Hong-Xing Yu, Ancong Wu, and W. Zheng. Cross-view asymmetric metric learning for unsupervised person re-identification. 2017 IEEE International Conference on Computer Vision (ICCV), pages 994–1002, 2017.

[30] Hong-Xing Yu, W. Zheng, Ancong Wu, X. Guo, S. Gong, and J. Lai. Unsupervised person re-identification by soft multilabel learning. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 2143–2152, 2019.

[31] Kaiwei Zeng, Munan Ning, Yaohua Wang, and Yang Guo. Hierarchical clustering with hard-batch triplet loss for person re-identification. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 13657–13665, 2020.

[32] Yunpeng Zhai, Qixiang Ye, Shijian Lu, Rongrong Ji, and Yonghong Tian. Multiple expert brainstorming for domain adaptive person re-identification. ArXiv, abs/2007.01546, 2020.

[33] L. Zheng, Liyue Shen, Lu Tian, S. Wang, Jingdong Wang, and Q. Tian. Scalable person re-identification: A benchmark. 2015 IEEE International Conference on Computer Vision (ICCV), pages 1116–1124, 2015.

[34] Zhedong Zheng, Xiaodong Yang, Zhiding Yu, L. Zheng, Y. Yang, and J. Kautz. Joint discriminative and generative learning for person re-identification. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 2133–2142, 2019.

[35] Zhedong Zheng, L. Zheng, and Y. Yang. Unlabeled samples generated by gan improve the person re-identification baseline in vitro. 2017 IEEE International Conference on Computer Vision (ICCV), pages 3774–3782, 2017.

[36] Zhan Zhong, L. Zheng, Donglin Cao, and Shaozi Li. Re-ranking person re-identification with k-reciprocal encoding. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 3652–3661, 2017.

[37] Zhan Zhong, L. Zheng, Zhiming Luo, Shaozi Li, and Y. Yang. Invariance matters: Exemplar memory for domain adaptive person re-identification. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 598–607, 2019.
[38] Zhun Zhong, L. Zheng, Zhiming Luo, Shaozi Li, and Yezhou Yang. Learning to adapt invariance in memory for person re-identification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 43:2723–2738, 2021.

[39] Kaiyang Zhou, Yongxin Yang, A. Cavallaro, and T. Xiaang. Omni-scale feature learning for person re-identification. *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 3701–3711, 2019.

[40] Yang Zou, Xiaodong Yang, Zhiding Yu, B. Kumar, and J. Kautz. Joint disentangling and adaptation for cross-domain person re-identification. *ArXiv*, abs/2007.10315, 2020.