Learning Domain Invariant Representations for Generalizable Person Re-Identification

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Abstract—Generalizable person Re-Identification (ReID) aims to learn ready-to-use cross-domain representations for direct cross-data evaluation, which has attracted growing attention in the recent computer vision (CV) community. In this work, we construct a structural causal model (SCM) among identity labels, identity-specific factors (clothing/shoes color etc.), and domain-specific factors (background, viewpoints etc.). According to the causal analysis, we propose a novel Domain Invariant Representation Learning for generalizable person Re-Identification (DIR-ReID) framework. Specifically, we propose to disentangle the identity-specific and domain-specific factors into two independent feature spaces, based on which an effective backdoor adjustment approximate implementation is proposed for serving as a causal intervention towards the SCM. Extensive experiments have been conducted, showing that DIR-ReID outperforms state-of-the-art (SOTA) methods on large-scale domain generalization (DG) ReID benchmarks.

Index Terms—Generalizable person re-Identification, disentanglement, backdoor adjustment.

I. INTRODUCTION

PERSON Re-IDentification (ReID) [1] aims at matching person images of the same identity across multiple camera views. In previous work, most ReID models are trained and tested on the same dataset, termed fully-supervised methods [2], [3], or adapted by the unlabeled data in target domains different from the training datasets, termed unsupervised domain adaptation (UDA) methods [4], [5]. Although recent fully-supervised methods have achieved remarkable performance, they tend to fail catastrophically when tested in out-of-distribution (OOD) settings. Fig. 1 illustrates the fragility of two representative fully-supervised models, i.e., the DG-Net [3] and ISGAN [6], which both get very high rank-1 accuracies when model training and test are performed on the same Market1501 dataset [7]. However, the rank-1 accuracies drop to 18.7% and 27.8% respectively when directly tested on the GRID dataset [8], which suggests the weak extrapolation capability and poor robustness of fully-supervised methods. We further train these two models over multiple source domains (the details of sources are in Section IV-A). However, the even worse performance are obtained, which indicates the challenge of ReID under the OOD settings. To tackle these problems, a number of UDA methods have been proposed to mitigate the domain gap without the need for extensive manual annotations in new target domains. However, they still need to collect large amounts of unlabeled data for UDA retraining. These problems severely hinder real-world applications of current person ReID techniques.

To tackle the above challenges, we focus on a more realistic and practical setting: generalizable person ReID, where the model is trained on multiple large-scale public datasets and on unseen domains directly without any model adaptations. The generalizable person ReID is originally formulated as a problem of domain generalization (DG) [9], which is more practicable than the traditional ReID paradigm since the ready-to-use models can work on any new settings without the requirement of data collection, annotation, and model updating.

Assuming that a person image can be factorized into two latent factors, i.e., the identity-specific factors $S$ (e.g., appearances, body shapes) and the domain-specific factors $V$
(e.g., imaging conditions such as backgrounds, viewing angles, illuminations etc.), we first present a structural causal model (SCM) for generalizable person ReID, which provide insights for the poor generalization of traditional ReID models when applied to unseen domains. Here, we highlight the potential reason for poor generalization ability: the domain-specific factors $V$ confound the identity-specific factors $S$ as well as the identity label $Y$, so that the spurious correlations between $V$ and $S$ hinder the model from making a robust prediction on identity label $Y$ based on $S$. Thus, a novel domain-invariant representation learning paradigm is proposed for generalizable person ReID, termed DIR-ReID, which disentangles the two latent factors $V$ and $S$ to remove the spurious features.

Specially, a Multi-Domain Disentangled Adversarial Neural Network (MDDAN) is first proposed to jointly learn two encoders for embedding identity-specific and domain-specific factors from multiple public ReID datasets, where the adversarial learning principle is adopted to exclude the domain-related information from the embedded identity specific representations. Then a differentiable backdoor adjustment block (BA) is proposed to approximate the interventional distribution [10], which can pursue the true causality between identity-specific factors and identity labels. These two components (MDDAN and BA) are integrated as an end-to-end learning framework for generalizable person ReID, namely DIR-ReID.

To sum up, the contributions of our work can be summarized as follows:

- For the first time, a causal perspective on the analysis of generalizable person ReID is introduced, by which the domain-specific factor is essentially a confounder that causes the spurious correlations between person features and identity labels in new target domains.
- Thanks to the above analysis, a novel domain-invariant representation learning framework is proposed for generalizable person ReID, namely DIR-ReID, where an MDDAN block is adopted to disentangle identity-specific and domain-specific factors from multiple data sources. Then a BA block is adopted to approximate causal interventions. Mathematical analysis proves the characteristics of our method;
- Comprehensive experiments are conducted to demonstrate the effectiveness of the proposed DIR-ReID model. Our method achieves superior performance in comparison with state-of-the-art (SOTA) methods on large-scale generalizable person ReID benchmarks.

II. RELATED WORK

A. Single-Domain Person ReID

Existing works of single-domain person ReID (i.e., supervised person ReID) usually depend on the assumption that training and testing data are independent and identically distributed. They usually design to learn discriminative features [11] or develop efficient metrics [12]. With the rapid development of deep Convolutional Neural Networks (CNNs), single-domain person ReID has achieved great progress. Some of the CNN-based methods introduce human parts [13], [14], poses [15], and masks [16] to improve the robustness of extracted features. Reference [17] propose a multi-level Context-aware Part Attention(CPA) model to learn discriminative and robust local part features. Reference [18] propose a Homogeneous Augmented Tri-Modal (HAT) learning method for visible modality and night-time infrared modality. Reference [19] introduces an online co-refining (CORE) framework with dynamic mutual learning. Reference [20] designs an intra-modality weighted-part attention (IWPA) to construct part-aggregated representation. And some other methods use deep metric learning to learn appropriate similarity measures [21].

Due to the space limitation, many important works cannot be covered. A well-summarized survey on person reID can be found at [1]. Despite the encouraging performance under the single-domain setup, current fully-supervised ReID models degrade significantly when deployed to an unseen domain.

B. Cross-Domain Person ReID

Unsupervised Domain Adaptation (UDA) technologies have great progress [22] and been widely adopted for cross-domain person ReID. The UDA-based ReID methods usually attempt to transfer the knowledge learned from the labeled source domains to target domains one depending on target-domain images [4], [23], features [24] or metrics [25]. Another group of UDA-based methods [26], [27] propose to explore hard or soft pseudo labels in the unlabeled target domain using its data distribution geometry. Though UDA-based methods improve the performance of cross-domain ReID to a certain extent, most of them require a large amount of unlabeled target data for model retraining.

C. Generalizable Person ReID

Recently, generalizable person ReID methods [9] are proposed to learn a model that can generalize to unseen domains without the requirement of model adaptation and data collection in target domains. Existing methods mainly follow a meta-learning pipeline or utilize domain-specific heuristics. Jia et al. [28] learn the domain-invariant features by integrating the Instance Normalization (IN) into the network to filter out style factors. Jin et al. [29] extend the work [28] by restituting the identity-relevant information to network to ensure the model discrimination. Lin et al. [30] propose a feature generalization mechanism by integrating the adversarial auto-encoder and Maximum Mean Discrepancy (MMD) alignment. Song et al. [9] propose a Domain-Invariant Mapping Network (DIMN) following the meta-learning pipeline. There also have some studies for learning domain-invariant features, e.g., DANN [31], DDAN [32] and CaNE [33]. The difference between DIR-ReID and these methods is detailed in Section III-F.

D. Domain Generalization

In the machine learning community, domain/OOD generalization [34], [35], [36] aims to learn representations $\Phi(X)$ that is invariant across environments $\mathcal{E}$ so that model can well extrapolate in unseen environments. The problem can
be formulated as \( \min_\Phi \max_{\epsilon \in E} \mathbb{E}[l(y, \Phi(x)) \mid E = \epsilon] \). Representative approaches such as IRM [37] have been proposed to tackle this challenge. However, IRM would fail catastrophically unless the test data are sufficiently similar to the training distribution [38]. To alleviate these challenges, we adopt a causal representation [39] framework termed DIR-ReID, to explicitly remove the confounding effects of spurious features via backdoor adjustment.

### E. Causality for CV

Causal Representation Learning [39] combines machine learning and causal inference and has attracted increasing attention within a learning paradigm for improving generalization and trustworthiness. Simultaneously, there is a growing number of CV tasks that benefit from causality [40], [41]. Most of them focus on measuring causal effects: disentangling the desired model effects [42], and modularizing reusable features that generalize well [43]. Recently, causal intervention is also introduced into some CV researches [44], [45], [46]. Specifically, CONTA [47] removes the confounding bias in image-level classification by backdoor adjustment and thus provides better pseudo-masks as ground truth for optimizing the subsequent segmentation model. IFSL [48] believes that pre-training is a confounding factor that hurts the few-shot learning (FSL) performance. Thus, they propose a SCM in the process of FSL and then develop three practical implementations based on the backdoor adjustment. We also adopt the SCM [49] to model the causal effects in generalizable person ReID, where the causal analysis clearly provides the explanations why traditional methods work poorly on unseen domains and then guides the design of the proposed DIR-ReID framework.

### III. LEARNING DISENTANGLED AND INvariant REPRESENTATIONS

In this section, we first introduce the proposed SCM to analyze the spurious correlations between domain-specific factors \( V \) and identity labels \( Y \). Then, a DIR-ReID framework is proposed to learn domain-invariant features for generalizable person ReID, where a BA block approximates the interventional distribution to capture the true causality between identity-specific factors \( S \) and identity labels \( Y \). Finally, a theoretical analysis is taken for a better understanding of our method.

#### A. SCM for Generalizable Person ReID

Inspired by current research of harnessing causality in machine learning [40], we propose an SCM to analyze the disentanglement and generalization in person ReID models.

Following the causal models in [50] and [51], we use the SCM (in Fig. 2(a)) to describe the causal relationships between person images and person identities, where \( Y \) denotes the observable variables of identity labels, \( S \) and \( V \) are the latent variables indicating identity-specific and domain-specific factors respectively. As shown in the model, there are three kinds of causal relationships as follows.

\[
S \rightarrow Y. \quad \text{Identity-specific factors } S \text{ directly cause } Y, \text{ which means the person identities are mainly determined by their identity-specific information, such as clothing styles, body shapes, etc.}
\]

\[
V \rightarrow S, V \rightarrow Y. \quad \text{In real scenarios, there are also some confounders } v_i \in V \text{ (e.g., backgrounds, illuminations, and viewpoints) that affect both identity-factors } S \text{ and person identities } Y. \text{ The } V \rightarrow S \text{ edge indicates the spurious correlations between } S \text{ and } V \text{ in the real world. } V \rightarrow Y \text{ denotes the influences of contextual environments in } V \text{ on } Y. \text{ For example, most pedestrians in CUHK03 dataset are captured by high-definition cameras on the campus. While for some early ReID datasets, e.g., GRID [8] and PRID [52], the low-resolution, varying illumination conditions, and various parameters of imaging devices (domain-specific factors) make the appearance of persons vary greatly, even for the same color clothes. For example, the pedestrians in column 1 of Fig. 3 are all wearing white, however, their appearance, such as clothing colors (identity-specific factors) will be influenced by some confounders in the domain-specific factors.} \]

\( ^1 \) The white cloth of \( P_1 \) in GRID is more yellowish and that of \( P_1 \) in PRID is more greenish.

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Fig. 2. Graphical representation of person ReID methods. \( S, V \): identity-specific and domain-specific factors, \( Y \): identity labels. Gray circles denote observable variables. (a) Traditional ReID model where \( P(Y|S) \neq P(Y|do(S)) \). (b) Interventional ReID model where \( P(Y|S) = P(Y|do(S)) \).

Fig. 3. Spurious correlations between domain-specific factors and identity-specific factors.
spurious correlations between $S$ and $V$ also confounds the prediction of identity labels $Y$.

An ideal ReID model should capture the true causality between $S$ and $Y$ which can be generalized to other unseen domains. However, from the SCM in Fig. 2(a), the conventional correlation $P(Y|S)$ fails to do so, because the likelihood of $Y$ given $S$ is not only influenced by “$S$ causes $Y$” via $S \rightarrow Y$, but also the spurious correlations via $V \rightarrow Y$. Therefore, to pursue the true causality between $S$ and $Y$, we need to adopt the causal intervention [10] $P(Y|do(S))$ instead of the likelihood $P(Y|S)$ for the ReID model.

B. Preliminaries of Causal Intervention

The causal intervention seeks the true causal effect of one variable on another, and it is appealing for the objective of DG ReID: given one pedestrian image $x_i$, we hope the model’s prediction (pedestrian entity) is faithful only to the semantic feature $S$, while removing the effects of spurious associations from domain-specific factors $V$. We use Fig. 2 for example, where the domain-specific factors $V$ (e.g., imaging conditions such as backgrounds, viewing angles, illuminations etc.) affect both $S$ and $Y$, leading to spurious correlations if only learning from $P(Y|S)$. To see this, by using the Bayes rule:

$$P(Y|S) = \sum_v P(Y|S,v)P(v|S), \quad (1)$$

where $v$ is an instance in $V$, which introduces the observational bias. Referring to the analyses in [44] and [45], we assume that the training dataset contains much more pedestrian identities from the CUHK03 dataset, where $S$ denotes the semantic information of one pedestrian and $v_{e,3} \in V$ the domain-specific factors of the CUHK03 dataset. After training, $P(v_{e,3}|S) \approx 1$, hence $P(Y|S) \approx P(Y|S, v_{e,3})$, which the supervised ReID methods actually do. Thus conventional ReID methods tend to build strong connections between the domain-specific factors and pedestrian identities in one domain, by which the ReID model is contaminated by the backdoor path $S \leftarrow V \rightarrow Y$.

Do-operation [49] removes certain relationships in the causal graph and replaces a factor with a constant. In our setting, the dependency between $V$ and $S$ should be cut off and the intervention posterior $P(Y|do(S))$ by applying do-operation will be:

$$P(Y|do(S)) = \sum_v P(Y|S,v)P(v). \quad (2)$$

Compared to Eq.(1), the key difference is that the adjustment weight $P(v|S)$ is changed to $P(v)$ because $V$ is no longer dependent on $S$. After the intervention cur-off (Fig. 2(b)). This encourages DG-ReID models to maximize $P(Y|S,v)$ for every style factor $v$, only subject to a prior $P(v)$.

C. Causal Intervention via Backdoor Adjustment

The above formulation only gives a causal quantity $P(Y|do(S))$ without further identification or grounding methods for computing it from purely statistical quantities. Therefore, we propose to use the backdoor adjustment [53] to identify and compute $P(Y|do(S))$ without the need for an ideal dataset. The back-door adjustment assumes that we can stratify the analysis by a number of confounding factors, i.e., $V = \{v_i\}_{i=1}^{|V|}$, where each $v_i$ is the domain-specific factor corresponding to a certain camera view, illumination condition, etc. Formally, the backdoor adjustment for the graph in Fig. 2(b) is (the detailed proof is shown in Appendix):

$$P(Y|do(S = s_k)) = \sum_{i=1}^{|V|} P(Y = s_k, V = v_i)P(V = v_i) \quad (3)$$

To calculate the above intervention distribution, there are still two challenges: (i) it is hard to instantiate $v$ and $s$, namely learning two embedding functions, $v_i = f_v(x_i)$ and $s_i = f_s(x_i)$ where $x_i$ is the $i$-th person image. (ii) it is almost impossible to enumerate all domain-specific factors $V$. Next, we will offer a practical implementation of Eq.(3): DIR-ReID.

D. The DIR-ReID Framework

1) Notations and Problem Formulation: For generalized person ReID, we have access to $G$ labeled datasets $D = \{D^g\}_{g=1}^G$. Each dataset $D^g = \{(x_i, y_i, d_i)\}_{i=1}^{N_g}$, where $N_g$ is the number of images in $D^g$. The i-th data sample in $D^g$ can be denoted as a triplet $(x_i, y_i, d_i)$, where $x_i$, $y_i$, $d_i$ denotes the image, identity label and the domain label respectively. In the training phase, we train a DG model using $N = \sum_{g=1}^G N_g$ aggregated image-label pairs from all source domains. In the testing phase, we perform a retrieval task on unseen target domains without additional model updates.

As analyzed in Section III-C, the challenges are (i) how to get the representations of $S$ and $V$ from observation $X$. (ii) how to approximately marginalize over the domain-specific factors $V$. Here, we propose DIR-ReID to tackle these challenges. DIR-ReID consists of two blocks, as shown in Fig. 4.

(i) Multi-Domain Disentangled Adversarial Neural Network (MDDAN): MDDAN consists of two subblocks: (1) Identity adversarial learning block, which is a domain-agnostic, identity-aware encoder $f_S$ to obtain identity-specific factors. (2) Domain factors learning block, which is a domain-aware encoder $f_V$ to identify domain-specific factors.

(ii) Backdoor adjustment block, which approximates the backdoor adjustment in Eq.(3) based on the disentangled representation space $V$ and $S$.

As shown in figure 4, the overall process includes feeding images $x_0, x_1, x_2$ randomly selected from $G$ source domain, into identity-specific and domain-specific encoders to get disentangled representations $s_0, s_1, s_2$ and $v_0, v_1, v_2$ via adversarial learning. Then backdoor adjustment is performed based on these representations to further train the encoders $f_S$ and $f_V$ for learning invariant representations.
2) **Identity Adversarial Learning Block:** An identity-aware encoder $f_S$ is adopted to extract identity-specific factors. Then, a classifier $C_S$ is used to identify the ID label for a given person image $x_i$. The cross-entropy loss with label smoothing [54] is calculated for training the encoder $f_S$, which is defined as:

$$L_{id}^i = - \sum_{i=1}^{N} \log P(Y = y_i | C_S(f_S(x_i)))$$

(4)

where $\theta_S$ is the parameters of $f_S$, $C_S$ is the identity classifier, $y_i$ is the labeled person identity of $x_i$. To exclude all the domain information from identity-specific factors, a domain classifier $C_V$ is adopted for adversarial learning. One promising way is using the gradient reversal layer (GRL) technique in DANN [31] to train the encoder $f_S$ and classifier $C_V$ simultaneously, where a misclassification loss is adopted to enforce an image not to be classified into its true domain class. However, a desirable disentangled representation should be “indistinguishability”, rather than “misclassification”, which means classifying the input into all the domains equiprobably. Hence, we adopt a loss of maximum entropy (minimization of negative entropy [50]) termed the domain-indistinguishability loss as follows:

$$L_{indis}^{dom} = - \mathcal{H}(D|S),$$

(5)

where $\mathcal{H}$ is the entropy to measure the uncertainty of predicted domain class given identity-specific factors, i.e.,

$$\mathcal{H}(D|S)) = - \sum_{i=1}^{N} P(D = d_i | C_V(f_S(x_i))) \cdot \log P(D = d_i | C_V(f_S(x_i))) ,$$

(6)

by which the extracted identity-specific features are required to reduce the domain information as less as possible.

As a result, the parameters $\theta_S$ of the identity-aware encoder $f_S$ are optimized by jointly minimizing the identity-classification loss and the domain-indistinguishability loss.

The overall objective function of identity adversarial learning is:

$$\min_{\theta_S} L_{id}^i + \lambda_1 L_{indis}^{dom},$$

(7)

where $\lambda_1$ is a hyper-parameter to balance the trade-off between two losses.

3) **Domain Factors Learning Block:** This block aims to extract the domain-specific factors from person images $x_i$.

The domain-classification loss $L_{dom}^i$ is defined as,

$$L_{dom}^i = - \sum_{i=1}^{N} \log P(D = d_i | C_V(f_V(x_i))),$$

(8)

where $d_i$ is the domain label of image $x_i$. The identity-indistinguishability loss $L_{indis}$ is similar to Eq.(6).

4) **Backdoor Adjustment Block:** With the disentangled representations learned from MDDAN, we can implement the backdoor adjustment. Given samples $\{x_i\}_{i=1}^N$, we first feed them to $f_S$ and $f_V$ to obtain $\{v_i\}_{i=1}^N$ and $\{s_i\}_{i=1}^N$. Then we follow two similar assumptions in [48].

(i) $P(v_i) = 1/|V|$, where we assume a uniform prior for the adjusted domain-specific factors.

(ii) $P(Y|S = s_i, V = v_k) = P(Y|s_i \oplus v_k)$, where $\oplus$ denotes vector concatenation.

Based on the above assumption, the overall backdoor adjustment is:

$$P(Y|do(S = s_i)) = \frac{1}{|V|} \sum_{k=1}^{K} P(Y|s_i \oplus v_k)$$

(9)

Here, to traverse all possible $V$, we propose 4 approximate implementations through random sampling over the feature space $V$.

- **K-Random.** For each $x_i$, we randomly select $K$ different domain-specific factors $\{v_k\}_{k=1}^K$.
- **K-Hardest.** For each $x_i$, we select $K$ domain-specific factors $\{v_k\}_{k=1}^K$ which are the most dissimilar to $v_i$. 

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**Fig. 4. Schematic description of the proposed approach.** $x_0, x_1, x_2$: Three images from one mini-batch. $f_S, f_V$: encoders of identity-specific and domain-specific factors. $s, v$: identity-specific and domain-specific factors represented in latent space. $C_S, C_V, C_d$: classifiers for identity-specific factors, domain-specific factors, and concatenated vectors. $\oplus$: concatenation of two latent vectors.
• $K$-Mixup. For each $x_i$, we can create more domain-specific factors by mixup [55], [56]. We generate $K$ mixed sample feature $v$ by interpolation of two randomly selected features (a pair $(v_k, v_k')$), denoted by

$$v = \alpha v_k + (1 - \alpha) v_k'$$

where $\alpha \in [0, 1]$ controls the interpolation degree and we empirically set $\alpha = 0.5$ in our experiments.

• $K$-MixHard. For each $x_i$, we firstly select $K$ domain-specific factors $(v_k)_{k=1}^K$ least like $v_i$ and generate $K$ mixed features by randomly interpolating these factors.

Then we can approximate the backdoor adjustment by

$$P(Y|do(S = s_i)) = \frac{1}{K} \sum_{k=1}^K P(Y|s_i \oplus v_k)$$

By ignoring the constant $1/K$, the final loss function is as follows.

$$L_{invar}^{id} = - \sum_i \sum_{k=1}^K \log P(Y = y_i \cap \mathbb{C}_C^S(s_i \oplus v_k)),$$

where the $\mathbb{C}_C^S$ is a classifier for the concatenated feature vectors.

$E$. Model Summary

Finally, given the parameters $\phi_S, \phi_V$ of classifiers $\mathbb{C}_S, \mathbb{C}_V$, the total loss function is summarized as follows.

$$\min_{\phi_S, \phi_V} L_i^{\text{id}} + L_{\text{dom}}^\text{id} + L_{\text{dom}}^\text{v}.$$ (13)

And the overall loss functions for the other components are defined as

$$\min_{\phi_S, \phi_V} L_i^{\text{id}} + \lambda_1 L_{\text{indis}}^\text{dom} + \lambda_2 L_{\text{invar}}^{\text{id}},$$

$$\min_{\phi_S, \phi_V} L_{\text{dom}}^\text{v} + \lambda_3 L_{\text{invar}}^{\text{id}},$$ (14)

where $\phi_S, \phi_V$ are parameters of classifiers $\mathbb{C}_C^S$ and $\mathbb{C}_C^V$ respectively. With the above components, each mini-batch training process is divided into two phases. In Phase I, the encoders $f_S$ and $f_V$ as well as the augmented data classifiers $\mathbb{C}_C^S$ and $\mathbb{C}_C^V$ are trained by Eq.(14), while $\mathbb{C}_S, \mathbb{C}_V$ are fixed. Then in Phase II, $\mathbb{C}_S, \mathbb{C}_V$ are trained by Eq.(13), while other components are fixed.

$F$. Model Analysis

In this section, we first give a theoretical analysis of MDDAN. Then, we state the differences between MDDAN and other adversarial leaning-based methods. Finally, we discuss the proposed BA block in comparison with other causal representation methods.

1) Theoretical Characteristics of MDDAN:

Lemma 1: Let $\tau$ denote one of the source domains, $s^j$ are identity-specific factors of images from the $j$-th domain. Let $p(s^j|\tau = i)$ be the class-conditional density function of the $j$-th domain given domain information $\tau = i$. It can be proved that carrying out the MDDAN will lead to

$$p(s^j|\tau = i) = p_j(s^j), \quad \forall s^j, i = 1, \ldots, G.$$ (15)

It indicates that in the latent space of identity-specific representation, the probability density will be invariant to different domains. Its class-conditional density function given any domains (e.g., $p(s^j|\tau = i)$) is just equal to its prior density function value in its own domain (e.g., $p_j(s^j)$), but not dependents on the domain variable $\tau$.

Proof: Referring to [5], we can prove the Lemma 1. All the analyses are conducted in the shared identity-specific representation space. We first prove the following lemma.

Lemma 2: When MDDAN is carried out to perform the adversarial learning in Eq.(6), given any identity-specific representation $s^j$ of an image from domain $\tau = i$, the conditional probability of any $\tau = i$ given $s^j$ will equal $1/G$, namely for any $i = 1, \ldots, G$, we have $p(\tau = i|s^j) = 1/G$.

Proof: Here we slightly abuse the notation: omitting the domain classifier $\mathbb{C}_V$ and $p(k|s^j)$ is equivalent to $p(\tau = k|s^j)$.

MDDAN is defined as follows.

$$\max_{\mathbb{C}_V} \sum_{k=1}^G p(k|s^j) \log p(\tau = k|s^j),$$

s.t. $\sum_{k=1}^G p(\tau = k|s^j) \geq 1 \forall k$. (16)

Let $H(p_k) = p_k \log p_k$, where $p_k = p(\tau = k|s^j)$. We simplify the above optimization problem as

$$\min_{\mathbb{C}_V} \sum_{k=1}^G H(p_k), \quad \text{s.t.} \quad \sum_{k=1}^G p_k = 1, \quad p_k \geq 0, \quad \forall k,$$ (17)

where $H(p_k)$ is convex as we have $H''(p_k) = 1/p_k \ln 2 > 0$. The sum of convex functions $\sum_{k=1}^G H(p_k)$ is also a convex function. Namely, this problem is a convex optimization problem. To prove the lemma, it is now equivalent to show that the minimum value of this convex optimization problem is obtained when $p_1 = p_2 = \ldots = p_G = 1/G$.

We use the augmented Lagrangian method to solve the problem, where the Lagrange function is defined as

$$L(p, \lambda) = \sum_{k=1}^G p_k \log p_k + \lambda \left( \sum_{k=1}^G p_k - 1 \right).$$ (18)

We take partial derivatives for each $p_k$ and get

$$\frac{\partial L(p, \lambda)}{\partial p_k} = \log p_k + \frac{1}{\ln 2} + \lambda = 0.$$ (19)

Then we have $p_k = 2^{-\lambda-1/\ln 2}$. As $\sum_{k=1}^G p_k = 1$, we have $G * 2^{-\lambda-1/\ln 2} = 1$, and thus $p_k = 1/G, i = 1, 2, \ldots, G$. Since the local minimum of the convex function is the global minimum, when $p_1 = p_2 = \ldots = p_G = 1/G, \sum_{k=1}^G H(p_k)$ achieves
the minimum value, \( \log \frac{1}{G} \). In other words, when MDDAN is carried out and achieves the maximum uncertainty, for all \( i = 1, \ldots, G \), we have \( p(\tau = i | s^j) = 1/G \).

Now we are ready to prove Lemma 1. We can calculate any domain \( \tau \)'s conditional probability given \( s^j \), which is

\[
p(\tau = i | s^j) = \frac{p(s^j | \tau = i) p(\tau = i)}{p_j(s^j)}, \quad \forall s^j \cap i = 1, \ldots, G,
\]

(20)

where \( p(s^j | \tau = i) \) denotes the conditional probability of \( s^j \) given domain information \( \tau = i \). \( p_j(s^j) \) denotes the probability function of the identity-specific representation in its domain \( \tau = j \), and \( p(\tau = i) \) is the prior probability of domain classes \( \tau = i \). Without generality, we set equal prior probability for each domain, namely \( p(\tau = i) = 1/G \). Further, from the Lemma III-F.1 we know that, optimizing MDDAN leads to \( p(\tau = i | s^j) = 1/G \) for all \( i = 1, \ldots, G \). Hence, 20 becomes

\[
1/G = \frac{p(s^j | \tau = i) 1/G}{p_j(s^j)}, \quad \forall s^j \cap i = 1, \ldots, G,
\]

\[
\Rightarrow p(s^j | \tau = i) = p_j(s^j), \quad \forall s^j \cap i = 1, \ldots, G,
\]

(21)

thus completing the proof.

Lemma 3: From the view of information theory, MDDAN is minimizing the mutual information between identity-specific factors \( S \) and domain information variables \( \tau \), namely \( \min \mathcal{I}(S, \tau) \).

Proof: Minimizing the mutual information between the identity-specific factors \( S \) and the domain information variables \( \tau \) is defined as

\[
\min \mathcal{I}(S, \tau) = \min \mathcal{H}(\tau) - \mathcal{H}(\tau | S)
\]

\[
= \min -\mathcal{H}(\tau | S)
\]

\[
= \max \mathcal{H}(\tau | S)
\]

(22)

The second line is derived since the entropy of domain distribution \( \mathcal{H}(\tau) \) is not related to our optimization, which is only related to the dataset statistics. Namely, our MDDAN is essentially minimizing the mutual information between the identity-specific factors and the domain information.

2) Comparison With Other Adversarial Learning-Based Methods: Here we discuss similar studies DANN [31], DDAN [32] and CaNE [33], which also use adversarial training to reduce domain divergence or nuisance divergence. There are three differences between our methods and them: (i) The implementation strategies are different. Given \( n \) domains, DANN [31] needs \( n \) binary classifiers to check which domain one image belongs to. DDAN [32] selects one central domain, using one binary classifier to check if one image belongs to the central (1) or peripheral (0) domain. CaNE [33] implements adversarial training in nuisance attributes (camera ID and video timestamps), where a reweighted form of negative entropy is implemented for taking the class imbalance issues into consideration. We directly use entropy maximization with one multi-domain classifier, which extends the assumption of binary classification in DANN. (ii) The roles of adversarial learning are different. In our work, the MDDAN is firstly performed to obtain an initial disentangled representation of the identity/domain-specific factors. Then, the MDDAN and BA block are implemented jointly to further optimize the disentangled representation. While other related work only uses adversarial training to enhance the invariance of learned representations to some nuisances.

3) Comparison With Disentanglement-Based Methods: Compared to [50], our method has mainly three differences (1) Setting. [50] focus on domain adaptation, which has only two domains, i.e., the source domain and the target domain and a set of images in the target domain can be used for domain adaptation during the training phase. Ours are domain generalization, which has multiple domains and the target domain is unseen during training. (2) Methodologies. [50] has one decoder and uses the Evidence Lower Bound (ELBO) loss for training, which is not required for MDDAN. Besides, [50] uses traditional adversarial training + GRL to exclude the domain-specific information and we use the domain-indistinguishability loss. (3) We provide mathematical explanations. Firstly, we prove that the global optimal solution of MDDAN will lead to the independence between identity-specific and domain-specific factors (Lemma 3.1). Secondly, we prove that MDDAN is equivalent to the minimization of mutual information between identity and domain factors (Lemma 3.3.).

There are also some other works on domain adaptation contributing to distinguishing domain-specific and domain-invariant features [57], however, [57] first estimates pseudo-labels for the examples in the target domain using the existing unsupervised domain adaptation algorithm and then learns the normalization layers for source and target domains separately. Though UDA-based methods improve the performance of cross-domain ReID to a certain extent, most of them require a large amount of unlabeled target data for model retraining, which is unrealistic for DG ReID.

4) Comparison With Other Causal Representation Learning Methods: DIR-Reid has a similar causal graph with [44], [45], and [48]. Reference [44], [45], and [48] describe the causal mechanism in various visual tasks, while the elements in the SCM and the implementation details are entirely different. (i) Elements in the SCM. The main differences are list in Table. I. As far as we know, it is the first attempt to use backdoor adjustment in the disentangled feature space (identity-specific and domain-specific feature spaces). (ii) Implementation details: the implementation of [45] is based on front-door adjustment. The implementation of [44] is simple yet efficient: they concatenate the causal feature with the features of all the confounders and then use the concatenated feature to predict the label. Reference [48] propose three kinds of implementations of backdoor adjustment, where the class-wise adjustment is most relevant to us. They concatenate the probabilistic combination of pretraining features of all classes with the causal feature to predict the label of the causal feature. The BA block in our work also implements backdoor adjustment by feature concatenation with a number of selected domain-specific feature vectors. Since it is untractable to get a well-defined confounder dictionary [44] or pretraining features.
for all class [48]. It is natural to simply adopt the domain’s feature as the confounder dictionary. However, it works poorly (the second row in Table VI), which indicates that it is indispensable to disentangle the identity-specific factors and domain-specific factors and use the proposed approximate implementations.

### IV. Experiments

**A. Datasets and Settings**

Following [9] and [28], we evaluate the DIR-ReID with multiple data sources (MS), where source domains cover five large-scale ReID datasets, including CUHK02 [58], CUHK03 [59], Market1501 [7], DukeMTMC-ReID [60], CUHK-SYSU PersonSearch [61]. Details of MS are summarized in Table II. The unseen test domains are VIPeR [62], PRID [52], QMUL GRID [8] and i-LIDS [63]. We follow the single-shot setting, where the number of probe/gallery images is summarized in Table III. The average rank-k (R-k) accuracy and mean Average Precision (mAP) over 10 random splits are reported based on the evaluation protocol. In this way, we simulate the real-world setting that a ReID model is trained with all the public datasets and evaluate the generalization capability to unseen domains. The detailed evaluation protocols are as follows.

**GRID** [8] contains 250 probe images and 250 true match images of the probes in the gallery. Besides, there are a total of 775 additional images that do not belong to any of the probes. We randomly take out 125 probe images. The remaining 125 probe images and 1025 (775 + 250) images in the gallery are used for testing.

**i-LIDS** [63] has two versions, images and sequences. The former is used in our experiments. It involves 300 different pedestrian pairs observed across two disjoint camera views 1 and 2 in public open space. We randomly select 60 pedestrian pairs, two images per pair are randomly selected as probe image and gallery image respectively.

**PRID2011** [52] has single-shot and multi-shot versions. We use the former in our experiments. The single-shot version has two camera views $A$ and $B$, which capture 385 and 749 pedestrians respectively. Only 200 pedestrians appear in both views. During the evaluation, 100 randomly identities presented in both views are selected, the remaining 100 identities in view $A$ constitute the probe set, and the remaining 649 identities in view $B$ constitute the gallery set.

**VIPeR** [62] contains 632 pedestrian image pairs. Each pair contains two images of the same individual seen from different camera views 1 and 2. Each image pair was taken from an arbitrary viewpoint under varying illumination conditions. To compare to other methods, we randomly select half of these identities from camera view 1 as probe images and their matched images in view 2 as gallery images.

**B. Implementation Details**

Following previous generalizable person ReID methods, we use MobileNetV2 [64] as the domain-specific encoder $f_V$ and use MobileNetV2 with IN layer [65] as identity-specific encoder $f_S$. Our classifiers $C_S$, $C_V$, $C_C$, $C_C$ are simply composed of a single fully-connected layer. Images are resized to $256 \times 128$ and the training batch size is set to 128. Random cropping, random flipping, and color jitter are applied as data augmentations. The label smoothing parameter is 0.1. SGD is used to train all the components from scratch with a learning rate of 0.02 and momentum of 0.9. The training process includes 150 epochs and the learning rate is divided by 10 after 100 epochs. At test time, DIR-ReID only involves identity-specific encoder $f_S$, which is of a comparable network size to most ReID methods. The tradeoff weights are set to $\lambda_2 = 0.1$ and $\lambda_1 = \lambda_3 = \lambda_4 = 1$ empirically.
for us because there has only one source domain. Thus we
domain. The setting of cross-domain Re-ID is challenging
data for training without any model adaptations in the target
target domain). It is different from the settings in UDA
datasets. Although data from the target domain are inaccessible
obtain the maximum entropy loss in MDDAN with the maximum
factors may be smaller within a single dataset than that of
consider each camera view as a single domain for training the
as far as we know, there are a few publications focusing on
person ReID generalization problem, including DIMN [9],
does not need any model adaptations with the data of the target
e.g., current UDA methods (e.g., MMT [26] achieves more than
It is noted that DIR-ReID still has a large margin with
considerations, the final performance of the whole DIR-
It is different from the settings in UDA
methods, all models in our comparisons only use the source
target domain). It is verified by comparisons with the dual DANN [31] block.
DukeMTMC-ReID, ‘COMB’: THE COMBINATION OF ViPeR, PRID, CUHK01, i-LIDS, and CAVIAR DATASETS.
‘C3’: CUHK03, ‘-’: NO REPORT. 1st and 2nd highest accuracy are indicated by BLUE and RED color
consider each camera view as a single domain for training the
MDDAN block. As the camera views in the same dataset may share similar imaging characteristics, e.g., background
evironments, and resolutions, the variations of domain-specific factors may be smaller within a single dataset than that of
It is noted that DIR-ReID still has a large margin with
current UDA methods (e.g., MMT [26] achieves more than
75% rank 1 accuracy in the “Market-to-Duke” dataset setting, which is much superior to current DG methods). DIR-ReID
do not need any model adaptations with the data of the target
domain, which significantly reduces the costs of large-scale
data collections in practical deployments of ReID models.

C. Comparisons Against State-of-the-Art

1) Comparison With Single Domain Methods: Many supervised
methods report high performance on large-scale benchmarks, but their performance is still poor on small-scale ones. We
select 6 representative models (labeled as ‘S’ in Table IV) in
comparisons, which are trained with the data splits in target
datasets. Although data from the target domain are inaccessible
for DIR-ReID, it achieves competitive or better performance
on all four benchmarks, which indicates that sufficient source
data and our model based on domain invariance learning can
alleviate the need for data from the target domain.

2) Comparison With DG Methods: Then, we compare DIR-
ReID with existing methods about generalizable person ReID.
As far as we know, there are a few publications focusing on
person ReID generalization problem, including DIMN [9],
DualNorm [28], [71] and DDAN [32]. From the third row in
Table IV, the DIR-ReID has achieved the best performance in
terms of mAP against other SOTA DG-ReID methods.
Although our method falls behind others on the i-LIDS and the
GRID datasets in terms of Rank-5 and Rank-10, the DIR-ReID
obtains the best Rank-1 performance on three of four datasets.
Interestingly, methods such as SNR [29] and AugMining [71]
perform very well in i-LIDS, while having low performance
in other datasets, which suggests the unstable generalization
abilities of their models. To further measure the generalization
ability, we adopt the worst-domain accuracy (WDA) proposed
in [77] for a comparison. From Table IV, we can find our
DIR-ReID achieves the highest WDA value with 47.8% rank-
1 accuracy, which demonstrates the superior generalization
ability of our model.

3) Comparison With Cross-Domain Re-ID Methods:
To further evaluate the generalization ability of our
approach, we also perform cross-domain ReID tests with
two large-scale datasets, i.e., Market1501 and DukeMTMC.
The experimental results are presented in Table V (‘Market1501→DukeMTMC” indicates that Market-1501 is a
labeled source domain and DukeMTMC-ReID is an unseen
target domain). It is different from the settings in UDA
methods, all models in our comparisons only use the source
data for training without any model adaptations in the target
domain. The setting of cross-domain Re-ID is challenging
for us because there has only one source domain. Thus we

D. Ablation Studies

There are two main components in the proposed DIR-ReID:
the MDDAN block and the BA block. Here, we first analyze
the effectiveness of each block respectively, then demonstrate
their contributions to the final performance of the whole DIR-
ReID model.

1) Effectiveness of MDDAN: The superiority of MDDAN is verified by comparisons with the dual DANN [31] block.
The latter means inserting the GRL layers between \( f_S \), \( C_V \) and \( f_V \), \( C_S \). Simultaneously, the dual DANN block replaces the maximum entropy loss in MDDAN with the maximum

| Methods          | Type | Source | VIPeR (V) | PRID (P) | GRID (G) | i-LIDS (I) |
|------------------|------|--------|-----------|----------|----------|------------|
| DeepRank [66]    | S    | Target | 58.5      | 74.9     | 67.0     | 56.8       |
| DNS [67]         | T    | Target | 57.3      | 74.4     | 64.9     | 55.3       |
| MT-Det [68]      | T    | Target | 47.5      | 73.1     | 62.9     | 50.4       |
| JL-MTL [67]      | T    | Target | 50.7      | 74.2     | 65.5     | 52.0       |
| SSM [69]         | T    | Target | 53.7      | 79.5     | 69.1     | 55.2       |
| SpindleNet [70]  | S    | Target | 58.3      | 74.1     | 83.2     | 67.0       |
| AugMining [71]   | DG   | MS     | 49.8      | 70.8     | 77.0     | 64.6       |
| DIMN [9]         | DG   | MS     | 51.2      | 72.0     | 76.0     | 65.7       |
| DualNorm [28]    | DG   | MS     | 53.9      | 62.4     | 75.3     | 62.4       |
| SNR [29]         | DG   | MS     | 52.9      | 61.3     | 52.1     | 66.5       |
| DDAN [32]        | DG   | MS     | 56.5      | 65.6     | 76.3     | 62.9       |
| DIR-ReID         | DG   | MS     | 58.5      | 76.9     | 83.3     | 67.0       |

| Method             | Market-1501 (single-source DG) | Market-Duke | Cross-Domain Re-ID | Single-domain DG |
|--------------------|---------------------------------|--------------|-------------------|------------------|
| IBN-ReID [72]      | 43.7                            | 59.1         | 65.2              | 52.7             |
| OSNet [73]         | 44.7                            | 59.6         | 65.4              | 52.2             |
| OSNet-BN [73]      | 47.9                            | 62.7         | 68.2              | 57.8             |
| CrossGrad [74]     | 48.5                            | 63.5         | 69.5              | 57.1             |
| QMCNet [75]        | 48.8                            | 63.5         | 69.5              | 57.1             |
| L2A-OT [76]        | 50.1                            | 64.0         | 70.1              | 57.8             |
| OSNet-AIN [73]     | 52.4                            | 66.1         | 71.2              | 58.9             |
| SNR [29]           | 55.1                            | 68.3         | 72.7              | 58.2             |
| DIR-ReID           | 54.5                            | 66.8         | 72.5              | 58.0             |

TABLE V

Performance (%) Comparison With the State-of-the-Art on the Cross-Domain ReID Problem. 1st and 2nd highest accuracy are indicated by BLUE and RED color.
TABLE VI

| PRID | VIPeR | i-LIDS | GRID |
|------|-------|--------|------|
| Baseline (DualNorm [28]) | 38.9 | 54.0 | 64.3 | 34.4 |
| w/ Dual DANN [31] | 41.0 | 53.3 | 66.2 | 35.4 |
| Improvements† | 2.1 | -0.7 | 1.9 | 1.0 |
| w/ Confounder Dict [44], [48] | 39.6 | 54.7 | 65.8 | 35.9 |
| Improvements† | 0.5 | 0.7 | 1.5 | 1.5 |
| w/ MDDAN | 42.7 | 56.5 | 65.7 | 36.6 |
| Improvements† | 3.8 | 2.5 | 1.4 | 2.2 |
| w/ BA | 43.8 | 61.4 | 68.2 | 40.2 |
| Improvements† | 4.9 | 7.4 | 3.9 | 5.8 |
| w/ Triplet Loss | 44.6 | 62.7 | 66.9 | 41.4 |
| Improvements† | 5.7 | 8.7 | 4.6 | 7.0 |

Fig. 5. Ablation study on BA block. The metric is the rank-1 accuracy on the GRID dataset. Considering the expensive cost of training with five datasets, all the models here are trained on three datasets, i.e., Market-1501, CUHK02 and CUHK03.

Table VI shows the performance improvements of BA and the results are shown in Fig. 7. K-Random is the simplest method while it works well, attaining 38.72% rank 1 accuracy when K = 20. K-MixHard outperforms other methods and attains 40.16% rank 1 accuracy, which verified the importance of mixup for data augmentation. However, as we increase the value of K, the performance will not be improved.

3) Ablation Study of Different Blocks: To evaluate the contribution of each component, we gradually add the MDDAN block to the baseline, and the overall ablation studies are reported in Table VI. The MDDAN improves the rank-1 accuracy from 34.4% to 36.6% in the grid dataset. The results in PRID, VIPeR, and i-LIDS datasets are consistently improved, which validates that the MDDAN removes some of the domain-specific information from the identity-specific representations and yields consistent generalization performance improvements. The BA provides greater improvement gains on three test datasets. It validates that BA can exclude domain-specific information efficiently. Besides, we conduct an ablation study on the triplet loss, which is also shown to boost performance, indicating that the metric learning method is orthogonal to our DIR-ReID framework (Last line in Table VI).

4) Ablation Studies of Every Loss Function: A thorough ablation is shown in Table VII. Incorporating the encoder $f_S$ for the encoder $f_S$, the performance of the baseline where only $L_{id}^*$ for $f_S$ exists can be improved from 47.98% to 50.38%. If we implement BA block only with $L_{id}^*$, $f_S$, and $f_V$ trained by $L_{id}^*$ or $L_{id}^* + L_{id}^*$, namely no constraint on $f_V$, the performance is similar to the baseline because the feature space is not disentangled well and the backdoor adjustment cannot attain better performance. Once $f_V$ is further trained by $L_{id}^*$, namely, $f_V$ is constrained to contain domain information, the performance gets better. Finally, the $L_{id}^*$ is incorporated and $f_S$ is forced to remove domain information, the proposed DIR-ReID attains the best performance in such a disentangled feature space.

We also conduct additional ablation studies on rotated MNIST. The dataset results are as follows:

E. Ablation Studies on Rotated MNIST

Since the ReID datasets are collected from real surveillance scenarios, complex data variations hinder us from analyzing
the characteristics of the proposed model for feature disentanglement. Thus, we perform additional studies on a controlled simple dataset, i.e., the rotated MNIST.

1) Dataset and Setting: To verify the capability of the DIR-ReID model to disentangle $S$ and $V$, we first construct rotated MNIST datasets following [78]. 100 images per class (10 classes totally) are randomly sampled from the MNIST training dataset, which is denoted by $M_{0°}$. We then rotated the images in $M_{0°}$ by 15, 30, 45, 60, and 75 degrees, creating five additional domains. Models are trained in $\{M_{0°}, \ldots, M_{60°}\}$ and tested on $M_{75°}$. To plot the latent subspaces directly without applying dimensionality reduction, we restrict the size of latent spaces for $S$, $V$ to 2 dimensions. In experiments, we train the MDDAN block with an additional reconstruction loss, which is enough to attain an encouraging result.

2) Architecture and Implementation Details: The architectures of the encoders, classifiers are displayed in Table VIII, Table IX respectively. Our model and the baseline model Dual DANN are trained for 500 epochs and the batch size is set to 100. Adam optimizer is used to train all the components from scratch with a learning rate of 0.001. We also use warmup to linearly increase the learning rate from 0 to 0.001 during the first 100 epochs of training.

3) Additional Experimental Results:

a) Analysis of MDDAN: As shown in Table VI, directly applying the dual GRL block benefits the generalization ability, while the proposed MDDAN improve the test accuracy on $M_{75°}$ dataset by an even more large margin, which is 11.8 points.
TABLE IX
IN THE ABLATION STUDIES ON ROTATED MINIST DATASET:
ARCHITECTURE OF CLASSIFIERS FOR ID-SPECIFIC FACTORS,
DOMAIN-SPECIFIC FACTORS, AND CONCATENATED
VECTORS. THE PARAMETER FOR LINEAR
IS OUTPUT FEATURES

| block     | details                  |
|-----------|--------------------------|
| For $C_V$ | ReLU,Linear(5)           |
| For $C_S$ | ReLU,Linear(10)          |
| For $C_D$ | ReLU,Linear(5)           |
| For $C_C$ | ReLU,Linear(5)           |

TABLE X
ABSTRACTION OF THREE DIFFERENT BLOCKS: DUAL GRL BLOCK,
OUR MDDAN BLOCK AND THE BA BLOCK. THE REPORTED
VALIDATION METRIC IS THE ACCURACY OF THE $M_{75^*}$
DATASET. THE BASELINE IS ONLY USING
THE ENCODER $F_S$ AND CLASSIFIER $C_S$

|                     | Test Accuracy on $M_{75^*}$ |
|---------------------|------------------------------|
| Baseline            | 46.4                         |
| w/ Dual DANN [31]   | 53.5                         |
| Improvements↑       | 7.1                          |
| w/ MDDAN            | 58.2                         |
| Improvements↑       | 11.8                         |
| w/ BA               | 61.9                         |
| Improvements↑       | 15.5                         |

Fig. 7. Ablation study of backdoor adjustment methods. The reported validation metric is the test accuracy of the $M_{75^*}$ dataset.

**b) Analysis of methods for backdoor adjustment:** The comparison results are shown in Fig. 7. Similar to BA for Re-ID, here K-MixHard attains the most superior performance, which is 61.9% test accuracy.

c) Ablation study of different blocks: By adding the multi-domain disentangled block and the backdoor adjustment block successively, we improve the generalization accuracy from 46.4% to 58.2% and 61.9% respectively (Table X), showing the effectiveness of the proposed model again.

d) Visualization analysis: The disentanglement results are visualized in Fig. 6. We can find a correlation between the rotation angle (domain labels) and the learned domain-specific features $V$ in Fig. 7(a), five domains are clustered into five distinct clusters, while in Fig. 7(b) no clustering is visible, which denotes the very weak correlations between $V$ and class labels. By contrast, in Fig. 7(c) no clustering is visible according to the domain labels of rotation angles. But Fig. 7(d) shows ten distinct clusters, where each cluster corresponds to a digit class. From these qualitative results, we conclude that the MDDAN is able to disentangle the information contained in the rotated MNIST dataset, where the learned latent subspaces indeed encode the domain (rotation angles) information and identity (digit classes) information respectively.

V. CONCLUSION AND FUTURE WORK

We propose a novel generalizable person ReID approach based on disentanglement and backdoor adjustment from a causal invariance learning framework. Specifically, a MDDAN block is proposed to disentangle identity-specific and domain-specific factors from multi-source ReID training data. We then propose a BA block to learn the interventional distribution and reduce the confounding effects via backdoor adjustment. The comprehensive experimental results show that DIR-ReID achieves state-of-the-art performance.

In future, we can improve the model performance with other regularization techniques. One promising way is to generate realistic images from the latent disentangled representations. The augmented feature vectors are guided by a reconstruction loss, which will further improve the disentanglement of identity-specific and domain-specific factors. These generated images can also be used for augmenting the training set. Besides, we will seek other methods for better disentanglement performance such as replacing the multi-domain adversarial learning with mutual information minimization [79] or $f$-divergence maximization [80].

APPENDIX

DERIVATION OF THE INTERVENTIONAL DISTRIBUTION

$P(Y|do(s))$ FOR THE PROPOSED CAUSAL GRAPH

The following proof is similar to [48] with three rules of do-calculus [81]: Insertion/deletion of observations, Action/observation exchange and Insertion/deletion of actions. For consistency, we describe these three rules as follows [48]:

Given a causal directed acyclic graph $G$, denote $X, Y, Z$ and $W$ be arbitrary disjoint sets of nodes. We use $G_{X}$ to denote the manipulated graph where all incoming arrows to node $X$ are deleted. Similarly $G_{X|Z}$ represents the graph where outgoing arrows from node $X$ are deleted. Lower case $x, y, z$ and $w$ denote specific values taken by each set of nodes: $X = x, Y = y, Z = z$ and $W = w$. For any interventional distribution compatible with $G$, we have the following three rules:

Rule 1: Insertion/deletion of observations:

$$P(y|do(x), z, w) = P(y|do(x), w), if (Y \perp\!\!\!\!\!\perp Z|X, W)_{G_{X}}$$

(23)

Rule 2: Action/observation exchange:

$$P(y|do(x), do(z), w) = P(y|do(x), z, w), if (Y \perp\!\!\!\!\!\perp Z|X, W)_{G_{X|Z}}$$

(24)

Rule 3: Insertion/deletion of actions:

$$P(y|do(x), do(z), w) = P(y|do(x), w), if (Y \perp\!\!\!\!\!\perp Z|X, W)_{G_{X|Z}(W)}$$

(25)
where \( Z(W) \) is a set of nodes in \( Z \) that are not ancestors of any \( W \)-node in \( G_X \).

In our causal formulation, the desired interventional distribution \( P(Y|do(S = s)) \) can be derived by:

\[
P(Y|do(S = s)) = \sum_v P(Y|do(S = s), V = v)P(V = v)
\]

\[
= \sum_v P(Y|do(S = s), V = v)P(V = v)
\]

\[
= \sum_v P(Y|S = s, V = v)P(V = v).
\]

(26)

where line 1 follows the law of total probability; line 2 uses Rule 3 to change the domain-invariant conditional distributions; line 3 uses Rule 2 to change the intervention term to observation as \( Y \subseteq V \) in \( G_X \).

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