Domain Agnostic Learning for Unbiased Authentication

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Abstract

Authentication is the task of confirming the matching relationship between a data instance and a given identity. Typical examples of authentication problems include face recognition and person re-identification. Data-driven authentication could be affected by undesired biases, i.e., the models are often trained in one domain (e.g., for people wearing spring outfits) while applied in other domains (e.g., they change the clothes to summer outfits). Previous works have made efforts to eliminate domain-difference. They typically assume domain annotations are provided, and all the domains share classes. However, for authentication, there could be a large number of domains shared by different identities/classes, and it is impossible to annotate these domains exhaustively. It could make domain-difference challenging to model and eliminate. In this paper, we propose a domain-agnostic method that eliminates domain-difference without domain labels. We alternately perform latent domain discovery and domain-difference elimination until our model no longer detects domain-difference. In our approach, the latent domains are discovered by learning the heterogeneous predictive relationships between inputs and outputs. Then domain-difference is eliminated in both class-dependent and class-independent components. Comprehensive empirical evaluation results are provided to demonstrate the effectiveness and superiority of our proposed method.

1 Introduction

Authentication is the problem of confirming whether the data instances match personal identities. There is a variety of authentication applications including face recognition [65], fingerprint verification [63], and person re-identification [2,66]. However, the data-driven authentication process often suffers from undesired biases. In particular, the verification model is usually trained in one domain and tested and verified in other domains, which could cause inconsistent prediction results due to domain difference/shift. For example, for person re-identification [2], the prediction could be compromised due to the seasonal outfits changing or the angle variation between a camera and a pedestrian [2]. Domain difference/shift can take many forms, including covariate shift (distribution difference in \(p(x)\), where \(x\) denotes the feature) [52], target/prior probability shift (difference in \(p(y)\), where \(y\) denotes the output target) [64, 53], conditional shift (difference in \(p(y | x)\)) [64], and joint shift (difference in \(p(y, x)\)) [43]. Domain transfer methods can be categorized into two types [12, 15]:

\(^*\)Dr. Liang participated in this work when he was at Tencent.
\(^2\)The seasonal outfits include four domains: spring, summer, autumn, and winter. The outfit and the shooting angle can be regarded as two types of domain-difference.
Table 1: An example of the assumptions of our proposed GCLDR problem. Each class set includes its unique classes. “Train”/“Test” denotes the data for training/testing. “Latent” suggests domain labels are absent.

| Latent Domain | Class Set 1 | Class Set 2 | Class Set 3 |
|---------------|-------------|-------------|-------------|
|               | Train       | Test        | Test        |
| Latent Domain 1 |            |             |             |
| Latent Domain 2 | Test        | Train       | Test        |
| Latent Domain 3 | Test        |             | Train       |

![Image](image.png)

(a) Training  
(b) Testing

Figure 1: An experiment setting of C-MNIST with the background color as the domain-difference. Best viewed in color.

1) symmetric methods that unify multiple domains into one common space; 2) asymmetric methods that map data from one domain to another. To understand how we can alleviate the aforementioned problem, we study the learning task for unbiased authentication. Specifically, we treat authentication as a recognition problem so that each identity corresponds to a class. For model efficiency, this paper focuses on the symmetric methods, eliminating domain-difference to unify domains.

The existing research on domain generalization [62, 22, 27, 18, 44, 28, 31, 30] or multi-domain adaptation [54, 13, 42, 13, 14] typically aims at learning domain-transfer from multiple training domains. One limitation of these approaches is that they assume domain labels are available. However, in real applications, it is labor-intensive and time-consuming to provide annotations of all domains, especially when the number of domains is massive. Therefore, researchers recently propose to detect the latent domains whose labels are absent [21, 29, 20, 41, 60, 45, 40]. These methods are typically purely based on features. However, the original reason why domain generalization/adaptation is essential is that the learned predictive relationship between features and targets, modeled by $p(y \mid x)$, on training data might change on testing data. Therefore, the key to understand domain difference is why the predictive relationship $p(y \mid x)$ is different in different domains. Consequently, to precisely learn and unify latent domains, we should exploit the heterogeneity in $p(y \mid x)$, in addition to the heterogeneity in features, as in most of the existing research.

Another limitation of existing approaches is that they require the classes for recognition to be shared across all the domains. However, since the classes are the identities, it is impossible to collect all domain data for every individual in the authentication task. The real scenario is that only the data from one domain are collected for each subset of individuals, and this phenomenon is characterized in the generalized cross-domain recognition (GCDR) problem [32], although they assume that domain labels are provided. In this paper, we propose to study the problem where domain labels are absent, which is referred to as a generalized cross-latent-domain recognition (GCLDR) problem. We present a toy example with only one type of latent domain difference in Table 1. Unlike the setups for standard domain generalization or adaptation, for training data in our example, different latent domains do not share any classes. For a colored-digit-recognition example shown in Fig. 1 in the training data set, one can only observe images of digits 0~4 with a green background, and digits 5~9 with a pink background, while the images of 5~9 with the green background are not observed. The background colors are the latent domains and do not share any digit in the training set. Consequently, for any testing data sample, a trained model could generate wrong prediction due to the misleading of its domain information. Thus, we should transfer knowledge across domains, then the recognition model trained on other latent domains can be used.

To address the above issues, we propose a novel domain-agnostic method to learn and unify latent domains to tackle the GCLDR problem. Specifically, we propose a latent-domain discovery (LDD) module to capture the heterogeneous predictive relationships between features and targets from different latent domains, where each predictive relationship comes from one latent domain. The LDD model also includes a domain-discrimination component, which discriminates latent domains based on features. The posterior distribution of latent domains given features and targets naturally integrates the recognition and domain-discrimination components via the Bayes rule such that
\( p(z \mid y, x) \propto p(y \mid x)p(z \mid x) \), where \( z \) denotes the latent domain. Thus, leveraging the predictive relationships \( p(y \mid x) \), we discover latent domains by the joint distribution \( p(y, x) \). By forcing the posterior probability of every latent domain to be equal, we can eliminate domain difference by the joint distribution \( p(y, x) \). We alternately perform the latent-domain discovery and unification processes. Therefore, every possible type of domain difference (e.g., season, and shooting angle) can be learned and eliminated successively. As a consequence, the number of latent domains, which is a hyper-parameter, can be robustly fixed to be two: as long as separated latent domains exist, they can be organized into two different groups. On the other hand, inspired by Liang et al. [32], we propose to eliminate latent domain-difference in both class-dependent and class-independent spaces in two branches of our network, respectively. This architecture can be more robust for domain-difference elimination. The experimental results on benchmark and real-world data sets demonstrate the effectiveness and superiority of our method. We also conduct ablation experiments to show the contribution of each component of our proposed framework.

2 Related Work

**Domain Generalization/Adaption**  Domain generalization approaches [62, 22, 27, 18, 44, 28, 31, 30, 51] typically train models on single/multi-domain data with shared classes for recognition on an unseen domain, while domain adaptation approaches [47, 17, 4, 38, 10, 55, 57, 37, 9, 58, 11, 7, 26] typically train models on source domains and recognize on target domains which share classes with source domains without class labels. Domain generalization and adaptation both typically assume that on training data, classes are shared across domains and domain labels are provided, which do not hold in our GCLDR problem.

**Domain Agnostic Learning**  Recently, several domain-agnostic learning approaches [48, 8, 36, 49] emerge to typically handle the domain-adaptation problem where the target domain may contain several sub-domains without domain labels [48]. DADA [48] and OCDA [36] propose novel mechanisms and achieve effective domain-adaptation performances, but do not discover latent domains in the target domain and exploit the information. By contrast, BTDA [8] clusters raw and deep features to discover latent domains. However, its latent-domain discovery is only feature-based and does not exploit the heterogeneous predictive relationships of \( p(y \mid x) \). DANL [49] learns a normalization layer, but may be limited for more sophisticated domain-difference [48]. Except for BTDA, these methods work on the extra knowledge of domain labels (source/target).

**Latent Domain Discovery**  Existing explicit latent-domain discovery approaches [21, 29, 20, 41, 60, 45, 40] typically build special models to learn latent domains explicitly based on features only. As an exception, Xiong et al. [60] propose to learn latent domains via a conditional distribution \( p(z \mid y, x) \), which is not based on the predictive relationship \( p(y \mid x) \), but based on linear addition of deep features of \( y \) and \( x \). When latent domains are discovered, a main-stream of these approaches does not perform domain transfer. However, as explained in introduction, it is not appropriate for our GCLDR problem. In contrast, mDA [41] (an improved version of DANL [49]) and its improved version CmDA [40] unify domains by normalizing the hidden space for each domain to have zero mean and unit standard deviation, which may be ineffective for more sophisticated domain-difference. In addition to the above explicit discovery methods, there are also several methods that learn latent domains implicitly, including ML-VAE [3], MCD [50] and MCD-SWD [24], which may encounter sub-optimal solutions due to not explicitly modeling multiple latent domains thus may ignore fine-grained information.

**Self-Supervised Learning**  Self-supervised learning typically formulates a auxiliary learning task [23, 19, 46, 6, 25, 19] to improve supervised-learning without class labels, and recently is found to be effective for generalization [33] or domain generalization/adaptation [5, 61]. However, it may suffer sub-optimal solutions in our GCLDR problem due to not explicitly modeling or unifying latent domains.

3 Methodology

This section lays out the details of our proposed network by first defining notations and problem settings. Consider a data set \( \mathcal{D} = \{(x_i^t, y_i^t)\}_{i=1}^n \) consisting of \( n \) independent samples. For the \( i \)th sample, \( x_i^t \in \mathbb{R}^d \) is a feature vector with \( d \) dimensions, and \( y_i^t \in \mathbb{Z}_+ \) is a categorical class label of the recognition task. The data set contains no domain labels. In other words, the setting of our proposed
GCLDR problem extends the GCDR problem [32] such that no domain labels are given. Throughout the paper, we denote $[k]$ as the index set $\{1, 2, \ldots, k\}$.

### 3.1 Heterogeneous Predictive Relationships Discovery and Unification

Our LDD module discovers multiple predictive relationships for $p(y \mid x)$. The discovery process utilizes the hidden features of a deep neural network. Here, we assume that we determine to discover $k \in \mathbb{Z}_+^+$ latent domains. Note that $k = 2$ is adequate, since we will discover and unify the rest of the latent domains successively. Given a hidden feature vector $f^i$ for the $i$th data sample $x^i$ ($i \in [n]$), we build $k$ local recognition networks $R^1_i, \ldots, R^k_i$ to learn $k$ conditional distributions of $p(y^i \mid f^i)$. Each conditional distribution corresponds to a subset of samples, and is denoted by $p(y^i \mid f, R^r_i)$ which follows a categorical distribution:

$$p(y^i \mid f^i, R^r_i) = \prod_{j=1}^c p(y^i = j \mid f^i, R^r_i)^{(y^i=r)}, r \in [k],$$

where $c$ denotes the number of classes. We further build a domain-discrimination network $D$ to discriminate which domain does $f^i$ belong to. Then $D$ aims to learn $p(z^i = r \mid f, D)$ for all $r \in [k]$, where $z^i$ denotes the latent domain for current $(y^i, f^i)$. Then via the Bayes rule, the posterior probability of $(y^i, f^i)$ belongs to the $r$th domain is

$$\rho^{i,r} = p(z^i = r \mid y^i, f^i, \{R^r_i\}_{r=1}^k, D) = \frac{p(z^i = r \mid f^i, D) \prod_{j=1}^c p(y^i = j \mid f^i, R^r_i)^{(y^i=r)}}{\sum_{r'=1}^k p(z^i = r' \mid f^i, D) \prod_{j=1}^c p(y^i = j \mid f^i, R^{r'}_i)^{(y^i=r')}}.$$  

(2)

The detailed derivation is in the supplementary material. We can observe in Eq. (3) that, since $f$ is based on $x$, the posterior probability models $p(z \mid y, x)$ which discover latent domains based on the joint distribution $p(y, x)$. Therefore, given class-label information, the posterior probability can provide more accurate domain-discrimination than the feature-based discriminative probability $p(z^i = r \mid f, D)$ which models $p(z \mid x)$ using the information of $p(x)$ only.

We aim to provide an end-to-end optimization scheme so that we discover latent domains on each mini-batch of data samples in a common mini-batch based optimization procedure. Given the posterior probabilities $\{\rho^{i,r}\}$ — soft selection of domains, we optimize:

$$\ell_d = -\frac{1}{b} \sum_{i=1}^b \sum_{r=1}^k \rho^{i,r} \sum_{j=1}^c I(y^i = j) \log p(y^i = j \mid f^i, R^r_i) - \frac{1}{b} \sum_{i=1}^b \sum_{r=1}^k \rho^{i,r} \log p(z^i = r \mid f^i, D),$$

(3)

where $b$ denotes the batch size, which is resulted from the Expectation-Maximization derivation (see supplementary material for details).

To unify latent domains, we propose to force the posterior probabilities to be equal across domains to eliminate domain-difference by the joint distribution $p(y, x)$:

$$\ell_e = \frac{1}{b} \sum_{i=1}^b \sum_{r=1}^k (p(z^i = r \mid y^i, f^i, \{R^r_i\}_{r=1}^k, D) - 1/k)^2.$$  

(4)

Alternately computing the posteriors by Eq. (2) and minimizing losses in Eq. (3) and (4), we can discover and then unify all the latent domains successively, until our model no longer detects domain-difference.

### 3.2 Double-Space Domain-Difference Elimination

Based on the latent-domain discovery and unification module introduced in Section 3.1, we propose to eliminate domain-difference both in a class-dependent space (where classes can be recognized) and a class-independent space (where classes cannot be recognized).

We first introduce our model structure to learn hidden features in the above two spaces. As shown in Fig. 2, an input sample $x^i$ is transformed by a mapping network $P$ into a hidden feature vector $f_c$, which is further transformed by two feature-extraction networks $G_{cd}, G_{ci}$ to obtain a class-dependent feature vector $f_{cd}^i$ and a class-independent feature vector $f_{ci}^i$, respectively. We let $f_{cd}^i$
be class-dependent by using a global recognition network $R_{g,cd}$ to recognize the class from $f_{cd}^i$ by minimizing:

$$
L_{cd} = \mathcal{L}_c(\{f_{cd}^i\}_{i=1}^b, R_{g,cd}),
$$

where $\mathcal{L}_c$ is defined in Eq. (3), $D$ are domain-discrimination networks, and $\{R_{l, cd}^k\}_{r=1}^k$ are groups of local recognition networks. Then we eliminate domain-difference in both class-dependence and class-independence spaces.

The domain-difference elimination is also realized via adversarial learning. According to Section 3.1, we discover latent domains in both class-specific and class-independence spaces by minimizing:

$$
L_d = \mathcal{L}_d(\{f_{cd}^i\}_{i=1}^b, \{R_{l, cd}^k\}_{r=1}^k, D_{cd}) + \mathcal{L}_d(\{f_{ci}^i\}_{i=1}^b, \{R_{l, ci}^k\}_{r=1}^k, D_{ci}),
$$

where $\mathcal{L}_d$ is defined in Eq. (6), $D$ are domain-discrimination networks, and $\{R_{l, cd}^k\}_{r=1}^k$ are groups of local recognition networks. Then we eliminate domain-difference in both class-dependence and class-independence spaces. We fix the LDD modules and learn $P, G_{cd}, G_{ci}$ by minimizing:

$$
L_u = \mathcal{L}_u(\{f_{cd}^i\}_{i=1}^b, \{R_{l, cd}^k\}_{r=1}^k, D_{cd}) + \mathcal{L}_u(\{f_{ci}^i\}_{i=1}^b, \{R_{l, ci}^k\}_{r=1}^k, D_{ci}),
$$

where $\mathcal{L}_u$ is defined in Eq. (4).

We summarize our latent-domain discovery and unification in double spaces in Algorithm 1. For inference, we stack $P, G_{cd}$ and $R_{g,cd}$ to predict the class label $y^i$ for each sample $x^i$.

4 Experiments

In this section, we evaluate our proposed framework. Both synthetic and real-world data sets are used for extensive evaluations. Our implementation uses Keras with Tensorflow backends.
We evaluate in the setting proposed by Liang et al. [32]: training domains do not share classes, and testing combinations of (class, domain) are different from those of training data. We conduct comprehensive evaluations on three data sets used by Liang et al. [32]: (1) the C-MNIST data set [39] with 10 classes and the background color as the domain-difference, (2) the re-organized CelebA data set [33] with 211 classes and whether wearing eyeglasses as the domain-difference, and (3) the authentication data set based on mobile sensors developed by Liang et al. [32] with 29 classes and the OS types as the domain-difference. The detailed re-organization process for each data set has been described by Liang et al. [32] and will be introduced in the following sections. Domain labels are not used. 10% data of the testing set are randomly selected for validation. For each method on each data set, we repeat 20 times and report the averaged results.

Evaluation Metrics We follow the settings of Liang et al. [32] to evaluate prediction performances for both multi-label and multi-class types of recognition. For the multi-label type, we use average AUC (aAUC) which is defined as the average of the area under the ROC curve for every class, the average false acceptance rate (aFAR), and the average false rejection rate (aFRR). We report aAUC and average balanced false rate (aBFR) = (aFAR + aFRR)/2 as balanced scores since the negative samples dominate for each class. For the multi-class type, we report top-1 accuracy (ACC@1).

Implementation Details We constrain our model-capacity to be the same as Liang et al. [32] to acquire fair comparisons. For all experiments, $G_{cd}$ and $G_{ci}$ are built by a single hidden layer with hyperbolic-tangent activation function, respectively. $R_{g,cd}$, $R_{g,ci}$, $\{R_{l,cd}^k\}_{r=1}^{b}$, $\{R_{l,ci}^k\}_{r=1}^{b}$, $D_{cd}$ and $D_{ci}$ are built by generalized linear layers, and using softmax as the activation function. For image data sets, $P$ is built by a convolutional neural network (CNN) with two convolutional layers. For vector based data sets, $P$ is built by a fully-connected neural network. We set $k = 2$ as discussed in the introduction. For the C-MNIST and the Mobile data set, the batch size is set to $b = 512$, while for the CelebA data set, $b = 128$.

### 4.1 Handwritten Digital Experiments

The C-MNIST data set is originally built by Lu et al. [39]. It consists of 70k colored RGB digital images with resolution of 28 × 28 (60k for training and 10k for testing). It is built from the original gray images of MNIST by adding 10 background colors (b-colors) and other 10 foreground colors (f-colors), resulting in 1k possible combinations (10 digits × 10 b-colors × 10 f-colors). Examples from C-MNIST are shown in Fig. 6 of Lu et al. [39]. Liang et al. [32] re-construct the C-MNIST data set for their GCDR problem. As shown in Fig. 4 training digits 0 ~ 4 have a green b-color, while 5 ~ 9 have a pink b-color. On the contrary, testing digits 0 ~ 4 have a pink b-color, while 5 ~ 9 have a green b-color. Other data are dropped. The re-construction results in 5970 training instances and 1003 testing instances in total.

Table summarizes the performance comparisons on C-MNIST. The results clearly show that our methods significantly outperform the direct learning method, which proves the effectiveness of our

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**Algorithm 1 Learning Algorithm for GCLDR**

Require: Data set $\mathcal{D} = \{(x^i, y^i)\}_{i=1}^n$, where $\forall i \in [n]$, $x^i \in \mathbb{R}^d$ and $y^i \in [c]$. Number of latent domains $k \in \mathbb{Z}_+$, Batch size $b \in \mathbb{Z}_+$.

Ensure: Recognition model: $R_{g,cd}(G_{cd}(P(\cdot)))$.

1: while not converge do
2: Sample a mini-batch $\{x^i, y^i\}_{i=1}^b$.
3: Forward the min-batch to obtain $f^i_{cd} = G_{cd}(P(x^i))$ and $f^i_{ci} = G_{ci}(P(x^i))$ for all $i \in [b]$.
4: Compute posteriors based on $\{f^i_{cd}\}_{i=1}^b$ and $\{f^i_{ci}\}_{i=1}^b$ by Eq. [2], respectively.
5: Optimize recognition and discrimination networks, i.e., $R_{g,cd}$, $R_{g,ci}$, $\{R_{l,cd}^k\}_{r=1}^{b}$, $\{R_{l,ci}^k\}_{r=1}^{b}$, $D_{cd}$, $D_{ci}$: $\min \mathcal{L}_{cd} + \mathcal{L}_{ci} + \mathcal{L}_{d}$, $\min \mathcal{L}_{cd} + \mathcal{L}_{ac} + \mathcal{L}_{u}$, respectively.
6: Optimize mapping and feature-extraction networks, i.e., $P, G_{cd}, G_{ci}$.

7: end while
Table 2: Performances (%) comparison on the C-MNIST data set. “∗” denotes the methods that use extra domain labels for training.

| Methods      | aAUC | aBFR | ACC@1 |
|--------------|------|------|-------|
| Direct       | 78.67| 26.32| 20.88 |
| "ABS-Net" [39] | 77.69| 27.41| 15.92 |
| "ELEGANT" [59] | 79.94| 24.61| 10.68 |
| "RevGrad" [16] | 80.71| 24.45| 21.68 |
| "CDRD" [34] | 84.83| 35.79| 33.49 |
| "AAL-UA" [32] | 98.42| 6.14 | 84.27 |
| "SE-GZSL" [56] | 99.79| 2.72 | 94.83 |
| MCD [50] | 49.90| 50.09| 10.89 |
| MCD-SWD [24] | 50.12| 49.89| 10.69 |
| ML-VAE [3] | 77.26| 28.06| 18.73 |
| DADA [48] | 83.90| 22.29| 15.83 |
| BTDA [8] | 85.14| 20.82| 26.43 |
| JiGen [5] | 82.44| 24.44| 33.33 |
| Rot [61] | 75.52| 36.41| 18.42 |
| MAXL [33] | 78.87| 25.28| 21.31 |
| mDA [41] | 83.34| 21.98| 24.26 |
| CmDA [40] | 86.52| 21.00| 43.21 |
| Ours | 93.46| 13.26| 60.63 |

Table 3: Performances (%) comparison on the CelebA data set. “∗” denotes the methods that use extra domain labels for training.

| Methods      | aAUC | aBFR | ACC@1 |
|--------------|------|------|-------|
| Direct       | 78.74| 41.58| 11.49 |
| "ABS-Net" [39] | 75.80| 34.90| 8.09  |
| "ELEGANT" [59] | 75.88| 32.02| 10.05 |
| "RevGrad" [16] | 80.12| 31.18| 10.96 |
| "CDRD" [34] | 80.20| 39.90| 16.47 |
| "SE-GZSL" [56] | 84.96| 26.62| 12.76 |
| AAL-UA [32] | 87.07| 22.19| 14.99 |
| MCD [50] | 50.16| 49.98| 0.45  |
| MCD-SWD [24] | 50.23| 50.15| 0.37  |
| ML-VAE [3] | 75.29| 36.07| 7.97  |
| DADA [48] | 83.37| 28.06| 11.36 |
| BTDA [8] | 78.23| 28.53| 8.30  |
| JiGen [5] | 81.94| 31.75| 10.57 |
| Rot [61] | 76.02| 34.37| 7.55  |
| MAXL [33] | 81.02| 28.26| 11.05 |
| mDA [41] | 80.19| 28.91| 10.90 |
| CmDA [40] | 83.57| 27.98| 11.79 |
| Ours | 88.52| 22.74| 22.31 |

methods. Furthermore, our methods significantly outperform the baseline methods that do not use domain labels for training, which shows the superiority of our proposed methods. Moreover, our methods even significantly outperform the majority of the baseline methods that use domain labels for training, except for the AAL-UA and the SE-GZSL methods. Considering these methods use additional domain labels, which renders it much easier for cross-domain recognition, these results provide sound evidence for the effectiveness and superiority of our methods. Fig. 3 shows some examples of generated hidden feature maps, in which the background difference is eliminated.

4.2 Face Recognition

We use the aligned, cropped and scaled version of the CelebA data set [35] with image-size of $64 \times 64$. Liang et al. [32] chose the Eyeglasses attribute as the domain-difference, selected individuals with at least 20 images, and balanced the data set such that $\#(\text{Eyeglasses} = 0)/\#(\text{Eyeglasses} = 1) \in [3/7, 7/3]$, resulting in 211 individuals. Half of the individuals wear glasses only during training, while the other half wear glasses only during testing. Table 3 shows the comparisons conducted on CelebA. We achieve consistent results with those in Table 2. Our methods significantly outperform the baseline methods without domain-label supervision and most baseline methods supervised by extra domain labels, which demonstrates the effectiveness and superiority of our methods. Note that our method even outperforms the best (AAL-UA) of the methods with domain-label supervision.

4.3 Authentication on Mobile Devices

We use the mobile data set built by Liang et al. [32] who collect smart-phone sensor information from 29 subjects, which records two-second time-series data from multiple sensors, such as accelerometer, gyroscope, gravimeter, etc. They extracted statistical features from both time and spectrum domains, resulting in 5144 data samples with the feature dimension of 191. They treated the OS types (IOS/Android) as the domain-difference and constructed a biased learning task, as shown in Table 4. The results are reported in Table 5, in which our methods still achieve consistent results. We can see that our methods significantly outperform the baseline methods without domain-label supervision and most baseline methods supervised by domain labels.

4.4 Ablative Study

We conduct a series of ablation experiments on the three data sets mentioned above to demonstrate how the heterogeneous predictive relationship discovery and the double-space domain-difference
Table 4: The authentication problem on mobile devices. The numbers in the first row indicate groups of subjects. “×” means there are no data for this condition.

| No. | IOS Train | IOS Test | Android Train | Android Test |
|-----|-----------|----------|---------------|--------------|
| 1-6 | ×         |          | ×             | Train        |
| 7-12|           |          | Android Train | Train        |
| 13-15|          |          | Android Train | Train        |
| 16-29|          |          | ×             | ×            |

Table 5: Performances (%) comparison on the Mobile data set. “∗” denotes the methods that use extra domain labels for training.

| Methods        | C-MNIST | CelebA | Mobile |
|----------------|---------|--------|--------|
| Direct         | 76.53   | 28.64  | 3.79   |
| RevGrad [16]   | 75.88   | 32.38  | 0.38   |
| ABS-Net [39]   | 76.58   | 28.09  | 5.13   |
| SE-GZSL [56]   | 78.83   | 26.12  | 20.54  |
| CDRD [34]      | 89.17   | 20.26  | 46.05  |
| AAL-UA [32]    | 93.40   | 13.59  | 46.37  |
| MCD [50]       | 83.12   | 21.37  | 24.35  |
| MCD-SWD [24]   | 84.49   | 19.89  | 25.35  |
| ML-VAE [3]     | 77.16   | 27.18  | 4.68   |
| DADA [48]      | 77.77   | 27.87  | 22.40  |
| BTDA [8]       | 86.96   | 17.85  | 30.21  |
| MAXL [33]      | 77.02   | 27.26  | 5.05   |
| mDA [41]       | 81.43   | 26.38  | 18.80  |
| CmDA [40]      | 82.22   | 21.84  | 20.42  |
| Ours           | 90.72   | 16.04  | 35.49  |

Table 6: The aAUC scores (%) of the ablation study for our method.

| Methods         | C-MNIST | CelebA | Mobile |
|-----------------|---------|--------|--------|
| Ours            | 93.46   | 88.52  | 90.72  |
| Single-Space    | 86.51   | 83.67  | 88.42  |
| Feature-Based   | 83.80   | 86.32  | 86.33  |
| Class-Confuse   | 77.48   | 75.63  | 75.13  |
| No-Unification  | 50.64   | 74.49  | 72.36  |
| Direct          | 78.35   | 78.54  | 76.90  |

elimination mechanisms contribute to the performance. We report the aAUC scores only due to space limitations. See the supplementary materials for more detailed results. Specifically, we compare the following four model variants of our method.

**Single-Space.** We learn and unify latent domains in the class-dependent space only.

**Feature-Based.** We learn and unify latent domains based on features only.

**Class-Confuse.** No latent-domain discovery and unification. But we still learn the class-independent space.

**No-Unification.** We discover latent domains but do not unify domains. Instead, for a testing sample, we select the recognition model from the most relevant domain to make recognition.

The results are presented in Table 6. It is notable that Feature-Based’s performances drastically decrease comparing with our best scores. The results demonstrate that using the class label to model the predictive relationship \( p(y \mid x) \) can harness more information, make a more accurate latent-domain discovery, and result in better class-alignment across latent domains. Besides, Our method outperforms Single-Space significantly, which shows that it is more robust to eliminate domain-difference both in the class-dependence and class-independence spaces. Liang et al. [32] also finds the effectiveness of such a multi-branch structure. Moreover, the results of Class-Confuse show that learning features in the class-independence space itself cannot contribute to cross-domain recognition, but rather slightly compromises the recognition performances comparing with the Direct method, because after all, its objective function is contrary to that of recognition. Lastly, the results of No-Unification are significantly worse than the Direct method, especially for the C-MNIST data set. It demonstrates that for our GCLDR problem when we only discover latent domains but do not unify them, a testing sample can only find a poorly trained recognition model from its domain, especially when latent domains are easy to discover.

5 Conclusion

In this paper, we investigate a generalized cross-latent-domain recognition problem in the field of authentication where domain labels are absent, and domains do not share classes. We recognize the class for unseen \( (\text{class, domain}) \) combinations of data. We propose an end-to-end domain agnostic method to tackle the problem. We build a heterogeneous predictive-relationship discovery and unification mechanism to discover and unify latent domains successively. Besides, we build a double-space domain-difference elimination mechanism to eliminate domain-difference in both class-dependent and class-independent spaces to improve robustness of elimination. The experiments
demonstrate that our method significantly outperforms existing state-of-the-art methods. We also conduct an ablation study to demonstrate the effectiveness of the critical components of our method.

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