Adversarial Training for Multi-domain Speaker Recognition

Qing Wang\textsuperscript{1}, Wei Rao\textsuperscript{2}, Pengcheng Guo\textsuperscript{1}, Lei Xie\textsuperscript{1,}\textsuperscript{*}

\textsuperscript{1}Audio, Speech and Language Processing Group (ASLP@NPU), School of Computer Science, Northwestern Polytechnical University, Xi’an, China
\textsuperscript{2}Tencent Media Lab, Shenzhen, China

\{qingwang, pcguo, lxie\}@nwpu-aslp.org, ellenrao@tencent.com

Abstract

In real-life applications, the performance of speaker recognition systems always degrades when there is a mismatch between training and evaluation data. Many domain adaptation methods have been successfully used for eliminating the domain mismatches in speaker recognition. However, usually both training and evaluation data themselves can be composed of several subsets. These inner variances of each dataset can also be considered as different domains. Different distributed subsets in source or target domain dataset can also cause multi-domain mismatches, which are influential to speaker recognition performance. In this study, we propose to use adversarial training for multi-domain speaker recognition to solve the domain mismatch and the dataset variance problems. By adopting the proposed method, we are able to obtain both multi-domain-invariant and speaker-discriminative speech representations for speaker recognition. Experimental results on DAC13 dataset indicate that the proposed method is not only effective to solve the multi-domain mismatch problem, but also outperforms the compared unsupervised domain adaptation methods.

Index Terms: multi-domain adaptation, adversarial training, speaker recognition

1. Introduction

In recent years, speaker recognition is becoming an important topic for biometrics, and a lot of techniques have been studied to improve its performance, such as i-vectors\textsuperscript{[1]} and x-vectors\textsuperscript{[2]}. However, like many machine learning tasks, speaker recognition system can be susceptible to performance degradation when substantial mismatch exists between the training and evaluation data. The population of interest (the evaluation data), is called target domain, for which the labels are usually not available, so it’s impossible to train a classifier directly. At the same time, if data from another population (the training data), whose labels are available, it could be used as source domain data. Thus, \textit{domain adaptation}\textsuperscript{[3]} is a common method to overcome the differences between domains so that the classifier trained on the source domain data generalizes well to the target domain data. When target domain labels are not available for training or fine-tuning, unsupervised domain adaptation becomes an alternative to improve the source domain trained model.

In speaker recognition area, many domain adaptation approaches have been successfully used to solve the domain mismatch problem\textsuperscript{[4,7]}. Most of these domain adaptation methods assume that the examples inside source or target domains are from the same distributions, however, usually the training and evaluation data are composed of several different datasets. Considering these data as a single domain will cause a sub-optimal solution, so eliminating mismatches among the multiple domain is vital. Multiple domain adaptation aims at obtaining a model with minimal average risk across multiple domains. Several studies have addressed this problem. In inter-dataset variability compensation (IDVC)\textsuperscript{[8]}, Aronowitz et al. found that the source domain dataset and target domain dataset could be composed of several subsets and there would be variances between the subsets. In\textsuperscript{[9]}, Pei et al. presented a multi-adversarial domain adaptation approach, which captures multimode structures to enable fine-grained alignment of different data distributions based on multiple domain discriminators instead of just based on the single discriminator. The adaptation can be achieved by stochastic gradient descent with the gradients computed by back-propagation in linear-time. In\textsuperscript{[10]}, Lin et al. proposed to use maximum mean discrepancy (MMD) to solve the problem of multiple source domains in speaker recognition. They adopted MMD to measure the discrepancies among multiple distributions and incorporated the discrepancy term into the objective function for training auto-encoders.

Domain adversarial training (DAT) was proposed by Ganin et al.\textsuperscript{[11,12]} to eliminate the domain mismatch in computer vision task, which inserted a gradient reverse layer (GRL) to learn both class-discriminative and domain-invariant intermediate representations in a multi-task framework. In recent studies, adversarial learning has been widely applied in speech related tasks\textsuperscript{[13,15]}. In speech recognition, Sun et al.\textsuperscript{[7]} proposed to use DAT in accented speech recognition. In\textsuperscript{[16]}, Guo et al. further refined the common DAT method by introducing an adversarial dropout regularization term. Hou et al.\textsuperscript{[19]} applied DAT to improve keyword spotting performance of ESL speech. In speaker recognition area, Wang et al.\textsuperscript{[20]} firstly proposed to use DAT to project source domain data and target domain data into a common space and extract domain-invariant and speaker-discriminative speech representations. Fang et al.\textsuperscript{[21]} learned the channel-invariant and speaker-discriminative representations via adversarial training. In\textsuperscript{[22,23]}, Tu et al. proposed variational domain adversarial neural network and information-maximized variational domain adversarial neural network to reduce domain mismatch.

In this study, we propose to use adversarial training for multi-domain speaker recognition. Due to the source and target domain data sets can be decomposed into several different subsets, instead of just solving the mismatch problem between source and target sets, we also take the inner variances of each dataset into consideration. In other words, we regard each subset as an independent domain and address this problem as a multi-domain mismatch in speaker recognition. Our goal is to reduce the differences among all the domains. In this multi-domain speaker recognition task, we mainly focus on three conditions of domain adaptation: multiple source domains with one target domain; one source domain with multiple
target domains; as well as multiple source domains with multi-
ple target domains. In order to extract multi-domain-invariant
and speaker-discriminative speech representations, we use ad-
versarial training for multi-domain adaptation. During training,
we use a multi-task framework, while the first task is the speaker
classifier and the second task is the multi-domain discriminator.
With gradient reversal layer (GRL) added before the domain
discriminator, the main network is not sensitive to multiple do-
 mains and projects the data from different domains into a same
subspace. Experiments on 2013 domain adaptation challenge
(DAC13) demonstrate that our proposed method can eliminate
the mismatches among all the domains.

2. Proposed method

2.1. Multi-domain adaptation by adversarial training

In unsupervised multi-domain adaptation task, we only have
the access to a source domain example \(x_{sn}\) and its correspond-
ing label \(y_{sn}\) drawn from different labeled sub-source domain
sets \(\{X_s, Y_s\} = \{(X_{s1}, Y_{s1}), \ldots, (X_{sN}, Y_{sN})\}\), in which \(N\)
means the number of sub-source domains. And a target sam-
ple \(x_{tn}\) drawn from different unlabeled sub-target domain sets
\(\{X_t\} = \{X_{t1}, \ldots, X_{tT}\}\), in which \(M\) means the number of
sub-target domains. The source domain and target domain set
themselves are decomposed into several subsets, which have
variances among each others. The mismatch problem is not
only between the distribution of source and target domains, but
also among the subsets from the source and target domains. In
order to solve these mismatch problems, we try to eliminate the
mismatch between the source and target domain as well as to
reduce the variance among different subsets.

Assume that we have the access to a set of labeled source
domain sample comes from \(N\) sub-source domains and a set of
unlabeled target domain samples from \(M\) sub-target domains
as defined before. When the number of source domain \(N\) and
target domain \(M\) are both equal to 1, the framework is the same
as conventional DAT in [20]. In order to eliminate the multi-
domain mismatches and dataset variances, we project the multi-
domains into a common subspace by multi-domain adver-
sarial training, which aims to learn speaker-discriminative and
multi-domain-invariant feature representations. The details of
the proposed method are shown in the following context.

The model can be decomposed into three parts as shown in
Figure 1 a feature generation network \(G\), which takes \(x_{sn}\)
or \(x_{tn}\) as the input; a speaker classifier \(C\), which takes source
domain samples’ features from \(G\) and classifies them into \(K\)
speaker classes; as well as a domain discriminator \(D\), which
predicts the specific domain label of the feature from \(G\). For
unsupervised domain adaptation task, only the labeled source
domain data are used to train the \(C\) and both source domain
and target domain data are used to update the \(D\). The mapping
functions can be formulated as: \(G(\mathbf{x}; \Theta_s), C(G(\mathbf{x}; \Theta_s); \Theta_c)\)
and \(D(G(\mathbf{x}; \Theta_s); \Theta_d)\), where \(\Theta_s, \Theta_c\) and \(\Theta_d\) are the pa-
rameters of the networks.

The following two requirements are satisfied in our method.
First, \(C\) and \(D\) are estimated to ensure that they will per-
form accurate speaker and domain classifications. Second,
\(G\) is used to extract speaker-discriminative and multi-domain-
invariant speech representations.

The objective function of the proposed model consists of
two parts. In the first part, \(G\) and \(C\) have to classify source sam-
pies into \(K\) classes of speakers correctly to obtain the speaker-
discriminative features. Thus, we update both networks’ param-
eters based on the following standard classification loss. Given
source domain sample \(x_{sn}\) and its speaker labels \(y_{sn}\), the objective function is:

\[
\min_{G,C} L_{cls} = -\mathbb{E}_{(x_{sn}, y_{sn}) \sim (X_s, Y_s)} \sum_{k=1}^{K} y_{sk} \log C(G(x_{sn}))_{k},
\]

where \(C(G(x_{sn}))_{k}\) returns the probability that the sample \(x_{sn}\) is
assigned to the class \(k\).

In the second part, \(D\) is trained as a discriminator to predict
the domain label of all the samples. The objective function of
this part is:

\[
\min_{D} L_{adv} = -\mathbb{E}_{x \sim (X_s, X_t)} \sum_{i} d_i \log D(G(x))_{i},
\]

where \(d_i\) refers to the domain label and \(D(G(x))_{i}\) returns the
probability of the sample \(x\) belonging to the \(i\)-th domain.

We are supposed to jointly train the \(G\), \(C\) and \(D\), and we
need to seek a \(\Theta_s\) to minimize the speaker classification’s ob-
jective function and to maximize the domain discriminator’s ob-
jective function at the same time. Since \(G\) should learn the
speaker-discriminative features for source domain samples as
well as multi-domain-invariant features for the samples from
all the domains. There is a gradient reversal layer (GRL) [12]
added between the feature generator \(G\) and the domain discrim-
inator \(D\) to search a saddle point between \(C\) and \(D\). The GRL
is multiplied by a certain \(\lambda\) during the back-propagation. \(\lambda\)
is a positive hyper-parameter used to trade off the losses. Gradi-
ent reversal layer ensures the feature distributions over different
domains approaching similar so that we can get multi-domain-
invariant and speaker-discriminative speech embeddings. The
final objective function is defined as:

\[
\min_{G} \max_{C, D} L = L_{cls} - \lambda L_{adv}.
\]
with other domain adaptation techniques, DAC2013 i-vector dataset is used in this study. Table 1 shows the details of DAC2013 i-vector dataset. The dimension of i-vectors is 600. Two datasets are defined for hyper-parameter training: 1) the source domain SWB set consists of all telephone calls from all speakers taken from the Switchboard-I and Switchboard-II (all phases) corpora; 2) the target domain SRE set consists of all the telephone calls without speaker labels are taken from the NIST SRE 04, 05, 06, and 08 collections, while SRE-1phn is a reduced set of SRE with only the i-vectors from 1 telephone number per speaker, which makes it hard to estimate within-class variability because of the lack of speaker and channel information. In this study, we selected the more challenging SRE-1phn data for the domain adaptation task. The telephone data of NIST SRE 2010 (SRE10) was selected as the evaluation set of DAC2013.

3.2. Data partition for multi-domain

Data partition is performed in two kind of manners. Firstly, following the work in [8], we divide the source domain data into 6 subsets based on the different LDC codes (LDC97S62 Switchboard-I Release2, LDC98S75 Switchboard-II Phase I, LDC99S79 Switchboard-II Phase II, LDC2002S06 Switchboard-II Phase III Audio, LDC2001S13 Switchboard Cellular Part 1 Audio and LDC2004S07 Switchboard Cellular Part 2 Audio). The second data partition manner is clustering. Because some of the data are recorded in the same year, but released in different subsets. We use k-means to cluster the source domain data into 3 subsets.

Because the target domain data is usually unlabeld, multi-target domain labels may not be accessed. So if we don’t have the prior information of the target domain, we did not partial the target domain data. When the prior information is available, we adopt the same strategies as mentioned above to divide the target domain data. The first one is based on the subset’s LDC codes (SRE2004, SRE2005, SRE2006, SRE2008). As a result, the target domain data is divided into 4 subsets according to the LDC distributions. Furthermore, k-means is also used to cluster the target domain data into 2 subsets.

3.3. Experimental setup

In unsupervised adversarial training for multi-domain speaker recognition experiments, the way we define the classes of multi-source and multi-target domain is shown in Table 2 where N and M indicate the numbers of multi-source domains and multi-target domains respectively. The conditions that with the multiple source domains only or with the multiple target domains only are denoted as MS-DAT and MT-DAT, respectively. In addition, MDAT is the condition of both source and target domains have multiple subsets.

For fair comparison, we use the same structure to all the DAT systems and we follow the setup in [20]. In the multi-domain adversarial neural network, there are two fully connected layers with 512 nodes for feature generation network G, two fully connected layers with 300 hidden nodes for speaker classification network C, and two fully connected layers with

![Figure 2: Block diagram of adversarial training for multi-domain speaker recognition.](image-url)

\[
\theta_y \leftarrow \theta_y - \mu \left( \frac{\partial L_{cls}}{\partial \theta_y} - \lambda \frac{\partial L_{adv}}{\partial \theta_y} \right),
\]

\[
\theta_c \leftarrow \theta_c - \mu \left( \frac{\partial L_{cls}}{\partial \theta_c} \right),
\]

\[
\theta_d \leftarrow \theta_d - \mu \left( \frac{\partial L_{adv}}{\partial \theta_d} \right),
\]

where \( \mu \) is the learning rate.

### 2.2. Adversarial training for multi-domain speaker recognition

In speaker recognition, the data we used to train the PLDA [24] are usually supposed to share the same distribution with the evaluation data, which are defined as target domain. However, in many scenarios, the target domain data are insufficient or the speaker labels are unavailable. So we propose to project multiple source and target domains into a common subspace, and we use the projected source domain data with speaker labels for the speaker recognition.

First, we use multiple source and target data to train the multi-domain adaptation neural network (MDANN). Since we don’t have speaker label of the target domain data, only the multi-source domain data is used to train the first task. The label of the first task is speaker ID. All the multi-source and multi-target domain data are used to train the second task. The label of the second task is subsets labels. After training the MDANN, we use multi-source domain vectors (\( x_s \)), multi-target domain vectors (\( x_t \)), enroll vectors (\( i_s \)) and test vectors (\( i_t \)) as the inputs to the MDANN and we use the representation of the hidden layer of the feature generation network as the new vectors (\( \hat{x}_s \), \( \hat{x}_t \), \( \hat{i}_s \), and \( \hat{i}_t \)) of all the data. The extracted embeddings are therefore expected to be multi-domain-invariant and speaker-discriminative speech representations which stand in the same subspace. Then, we apply the pre-processing (whitening and length-normalization [25]) to the \( x_s, \hat{x}_s, i_s \) and \( \hat{i}_s \). Finally, we use a scoring function to compute the scores between the speaker model and the test sample. In this paper, we adopt PLDA as the scoring method. Figure 2 shows how we use the proposed strategy in speaker recognition.

### 3. Experimental setup

#### 3.1. Dataset

We use the 2013 domain adaptation challenge (DAC2013) dataset [20] as the evaluation data set. DAC2013 is designed based on LDC telephone corpora and targeted the domain adaptation. It focuses on the effect of dataset mismatch on hyper-parameters, such as the latent speaker and channel factors for PLDA. Both the audio lists and i-vectors of NIST SRE data [27] and Switchboard data [28] are provided. For fair comparison, we select the NIST SRE data as the evaluation data and we follow the setup in [20]. In the multi-domain adversarial neural network, there are two fully connected layers with 512 nodes for feature generation network G, two fully connected layers with 300 hidden nodes for speaker classification network C, and two fully connected layers with

### Table 1: i-vector statistic in DAC 13 i-vector dataset

|       | SWB     | SRE    | SRE-1phn |
|-------|---------|--------|----------|
| #spks | 3114    | 3790   | 3787     |
| #calls| 33039   | 36470  | 25640    |
| #calls/spkrs | 10.6  | 9.6    | 6.77     |
| #phone_num/spkrs | 3.8  | 2.8    | 1.0      |
Table 2: Unsupervised multiple domain adaptation with adversarial training setup

| Adaptation Methods       | N | M |
|--------------------------|---|---|
| DAT [20]                 | 1 | 1 |
| MS-DAT (based on LDC code)| 6 | 1 |
| MT-DAT (based on LDC code)| 6 | 4 |
| MDAT (based on k-means)  | 3 | 1 |
| MT-DAT (based on k-means) | 1 | 2 |
| MDAT (based on k-means)  | 3 | 2 |

512 hidden nodes for domain discrimination network $D$.

In the training stage, we use SWB with speaker labels as multi-source domain data and SRE-1phn with no speaker label as multi-target domain data for the MDANN training, and use the subset domain labels as the supervised information of the second task. During the test stage, we use SWB, SRE-1phn, enroll and test data as the inputs of the network and extract the multi-domain-invariant and speaker-discriminative speech representation from the first hidden layer of the feature generation network $G$. After that the new SRE-1phn data is used for the whitening and centering to all the new data, and the PLDA back-end is trained using new SWB data with its speaker labels to obtain the scores.

4. Experimental results and analysis

4.1. Result of baseline

Table 3 shows the performance of the SRE10 c2-extended test when the parameters are trained with different datasets using the i-vector PLDA framework. System 1 can be considered as the desired benchmark when the in-domain dataset speaker label is known. System 2 is the baseline of the domain mismatched condition when the in-domain database is unlabeled. Systems 3 and 4 are versions of systems 1 and 2, respectively on more challenging conditions. System 3 is adapted using a matched in-domain labeled dataset SRE-1phn which is subset of SRE. Note that, although system 3 is under domain matched conditions and system 4 is under matched conditions, system 4 shows better performance in EER than system 3. This is an interesting result and we believe that performance was degraded by insufficient channel information. The dataset ‘SRE-1phn’ contains audio from only a single telephone number per speaker and use of such a poor phone number diversity hinders the effective estimation of within-speaker variability of in-domain.

Table 3: Results of DAC 2013 i-vector dataset without domain adaptation

| Systems | PLDA | EER (%) | DCF10 | DCF08 |
|---------|------|---------|-------|-------|
| 1       | SRE  | 2.33    | 0.402 | 0.235 |
| 2       | SWB  | 5.65    | 0.632 | 0.427 |
| 3       | SRE-1phn | 9.35  | 0.724 | 0.520 |
| 4       | SWB  | 5.66    | 0.633 | 0.427 |

4.2. Result of proposed method

The experimental results are given in Table 4. As a comparison, the first five systems are other domain adaptation methods [7] in speaker recognition. The system DAT is when the number of sub-source and sub-target domain are both equal to 1, which is the conventional domain adversarial neural network in [20]. The last six systems are multi-domain adversarial training experiments. The configurations of them are shown in Table 4. The experimental results demonstrate that, by projecting the multi-source domain data and multi-target domain data to a common space with the proposed approach, we can achieve the lowest EER, DCF10 and DCF08 compared to the conventional DAT [20] and other adaptation methods [7]. And almost all the systems of our method outperform the conventional DAT.

When the inner variances of both source and target domain are considered, we can get the best performance in system MS-DAT (based on LDC code or k-means). With the adversarial training for multi-domain speaker recognition, the EER is improved from 5.66% to 3.58%, with +36.7% relative error reduction compared to the baseline system, and also outperforms other compared domain adaptation techniques. Especially, comparing to the the traditional DAT in [20], +4.0% relative error reduction on EER, and a +11.6% relative improvement on DCF10, as well as a +10.7% relative improvement on DCF08 are achieved by this solution. The experimental results indicate that when both of multi-source and multi-target domain information is taken into consideration, domain mismatches and data variability can be largely alleviated. Considering the inner variances of each datasets makes the domain adaptation more efficient and can help to project the samples of all the domains into a more common space.

5. Conclusions

In this study, we proposed adversarial training for multi-domain speaker recognition to eliminate multi-domain mismatches among different subsets in speaker recognition. Compared to previous domain adaptation studies, we take inner dataset variance into consideration and extract multi-domain-invariant and speaker-discriminative representations for the speaker recognition. With the proposed methods, we obtained +36.7% and +4.0% relative EER improvement compared to baseline system and conventional DAT method respectively. Moreover, our approach improved DCF10 and DCF08 yields up to +11.6% and +10.7% compared to DAT. These results suggest the effectiveness of the multi-domain-invariant and speaker-discriminative speech representations in speaker recognition. In our future work, we will combine our method with teacher-student learning and conduct experiments on more complex scenarios.
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