SQUEEZING VALUE OF CROSS-DOMAIN LABELS: A DECOUPLED SCORING APPROACH FOR SPEAKER VERIFICATION

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ABSTRACT

Domain mismatch often occurs in real applications and causes serious performance reduction on speaker verification systems. The common wisdom is to collect cross-domain data and train a multi-domain PLDA model, with the hope to learn a domain-independent speaker subspace. In this paper, we firstly present an empirical study to show that simply adding cross-domain data does not help performance in conditions with enrollment-test mismatch. Careful analysis shows that this striking result is caused by the incoherent statistics between the enrollment and test conditions. Based on this analysis, we present a decoupled scoring approach that can maximally squeeze the value of cross-domain labels and obtain optimal verification scores when the enrollment and test are mismatched. When the statistics are coherent, the new formulation falls back to the conventional PLDA. Experimental results on cross-channel test show that the proposed approach is highly effective and is a principle solution to domain mismatch.

Index Terms— speaker verification, domain mismatch, decoupled scoring

1. INTRODUCTION

Speaker verification aims to recognize claimed identities of speakers. After decades of research, current speaker verification systems have achieved rather satisfactory performance, especially with the i-vector model [1], or embedding models based on deep neural nets (DNNs), e.g., the x-vector model [2][3]. The deep embedding models have been significantly improved recently, by employing advanced techniques such as novel architectures [4][5], attentive pooling [3][6][7], or max-margin training [8][9][10][11]. As a result, deep learning models have achieved state-of-the-art performance on several benchmark datasets [12], in particular when combined with the PLDA model [13] for scoring.

In spite of the great achievement, a large performance degradation is often observed when current speaker verification systems are deployed to real applications. A particular problem is domain mismatch, including the training-deployment domain mismatch and enrollment-test domain mismatch. For example, when the enrollment uses one recording device and the test uses another device, the performance will be seriously degraded.

A large body of research has been conducted to solve domain mismatch problem, and the basic idea among these approaches is either normalization or adaptation: the former aims to make the data or model domain-independent [14][15][16][17][18], while the latter aims to make them more suitable for the target domain [19][20][21]. Among all these approaches, training a multi-domain PLDA is commonly used. This approach collects data from multiple domains and then trains the PLDA model, with the hope to learn a domain-independent speaker subspace. This PLDA multi-domain training (MDT) is in particular useful when the training data is too limited to conduct more data-hungry approaches, e.g., the domain-invariant feature learning [15][18]. A key advantage of this MDT approach is that the resultant PLDA model will be suitable for both training-deployment mismatch and enrollment-test mismatch. Besides, domain-adaption training (DAT) is another approach, which transforms speaker vectors from source domain to target domain, and then performs the scoring process in target domain. The transform can be established based on maximum likelihood estimation.

For both MDT and DAT, cross-domain speakers are essentially important. The cross-domain labels provide information regarding the variation related to domains. A common wisdom is to collect as much cross-domain data as possible, with the hope to learn a true speaker subspace that is independent of domain change. However, our experimental study shows that this is not true: more cross-domain data does not necessarily lead to better performance in conditions with enrollment-test mismatch. We give a careful analysis on this phenomenon, and find that it is related to the statistics incoherence problem caused by domain mismatch. Based on this analysis, we propose a decoupled scoring approach. The key idea is to decouple the scoring process into different phases and utilize its own correct statistics in each phase. By this model, the cross-domain labels are only used to establish the link between the statistics of different domains.

The rest of this paper is organized as follows. Section 2 presents experimental setups, and Section 3 gives an empirical study on the statistics incoherence problem. Section 4 presets details of our proposed decoupled scoring approach. Section 5 describes experimental results, and the entire paper
2. EXPERIMENTAL SETUPS

2.1. Data

Two datasets were used in our experiments: VoxCeleb [4,22] and AIShell-1 [23]. VoxCeleb was used to train the speaker embedding model, which is the x-vector model in our experiment. AIShell-1 was used for performance evaluation under cross-channel domain mismatch scenarios. More information about datasets is presented below.

VoxCeleb: The entire dataset contains 2,000+ hours of speech signals from 7,000+ speakers. Data augmentation was applied to improve robustness, with the MUSAN corpus used to generate noisy utterances, and the room impulse responses (RIRS) corpus was used to generate reverberant utterances.

AIShell-1: This is an open-source multi-channel Chinese Mandarin speech dataset published by AISHELL. All the speech utterances are recorded in parallel via three categories of devices, including high fidelity Microphones (Mic), Android phones (AND) and Apple iPhones (iOS). This dataset is used for the cross-channel (domain) test in our experiment. The entire dataset consists of two parts: AIShell-1.Train, which covers 3 devices and involves 360,897 utterances from 340 speakers, was used to implement both the ad-hoc normalization/adaptation methods and our proposed decoupled scoring method. AIShell-1.Eval, which also covers 3 devices and involves 64,495 utterances from 60 speakers, was used for performance evaluation on cross-channel conditions.

2.2. Embedding models

We built the state-of-the-art x-vector embedding model based on the TDNN architecture [2]. This x-vector model was created using the Kaldi toolkit, following the VoxCeleb recipe. The main architecture contains three components, including feature-learning component, statistical pooling component and speaker-classification component. Once trained, the 512-dimensional activations of the penultimate layer are read out as an x-vector.

3. EMPIRICAL ANALYSIS

We firstly employ MDT approach to train a domain-independent PLDA. In detail, data of speakers collected from two domains are labeled in two ways. One is domain-independent labeling, where data from different domains shares the same speaker label. The other one is domain-dependent labeling, where data from different domains is relabeled as different speakers even if they are from the same speaker. The PLDA model will be trained in a controlled way, where we control the proportion of domain-independent and domain-dependent labels.

The expectation is that more domain-independent labels will lead to better performance at least in cross-domain test.

In our experiments, MDT is conducted using AIShell-1.Dev, and the resultant PLDA is evaluated on AIShell-1.Eval. Results are shown in Table 1. Note that in the first column, the case name ‘A-B’ means enrollment on condition A and test on condition B. The ‘Base’ column presents results using PLDA trained with the enrollment-matched development dataset. A key observation is that the best performance is obtained when the PLDA model is trained with 40%-60% domain-independent labels plus 60%-40% domain-dependent labels, rather with 100% domain-independent labels.

This somewhat striking result can be intuitively explained by the statistical nature of the PLDA model. Basically, PLDA conducts inference based on the between-class and within-class distributions that are learned from data, and if the distributions match the data perfectly, PLDA will derive optimal scores in terms of Bayes risk. Unfortunately, MDT learns distributions of the pooled data, which are not ideal for any domain. For instance, the within-class variance tends to be large by MDT even if it is small in each of the single domain, which may lead to unreliable scores. This analysis is just intuitive; more theoretical explanation will present in Section 4.

4. DECOUPLED SCORING

We present a theoretical analysis and solution for domain mismatch problem as mentioned in the previous section. This analysis and solution are based on the normalized likelihood (NL) scoring framework that we proposed recently [24].

4.1. Revisit NL scoring

The task of speaker verification is to test the following two hypotheses regarding to a speaker vector $x$ and check which one is more probable: \( H_0: x \) belongs to class $k$; \( H_1: x \) belongs to any class other than $k$. We therefore define the normalized likelihood (NL) as:

\[
NL(x|k) = \frac{p(x|H_0)}{p(x|H_1)} = \frac{p_k(x)}{p(x)}
\]  (1)

Table 1. EER(%) results with MDT under different cross-channel labels.

| Cases        | Base | Proportion of domain-independent labels |
|--------------|------|----------------------------------------|
|              | 0%   | 20%         | 40% | 60% | 80% | 100% |
| AND-AND      | 0.797 | -           | -   | -   | -   | -    |
| AND-Mic      | 2.146 | 3.329       | 1.410 | 1.273 | 1.066 | 1.259 | 1.151 |
| AND-iOS      | 1.425 | 1.642       | 1.104 | 0.930 | 1.029 | 1.170 | 1.161 |
| Mic-AND      | 2.175 | 3.675       | 1.953 | 1.746 | 1.184 | 1.307 | 1.161 |
| Mic-Mic      | 0.778 | -           | -   | -   | -   | -    |
| Mic-iOS      | 2.251 | 3.723       | 1.883 | 1.675 | 1.255 | 1.349 | 1.293 |
| iOS-AND      | 1.599 | 2.024       | 1.472 | 1.241 | 1.156 | 1.274 | 1.156 |
| iOS-Mic      | 2.216 | 3.697       | 1.651 | 1.476 | 1.061 | 1.236 | 1.137 |
| iOS-iOS      | 0.920 | -           | -   | -   | -   | -    |
where \( p(x|H_0) \) is the likelihood of \( x \) generated by class \( k \), denoted by \( p_k(x) \). The posterior for \( H_0 \) is essentially the likelihood \( p_k(x) \) normalized by the evidence \( p(x) \).

Assume a simple linear Gaussian to implement the NL score as follows:

\[
p(\mu) = N(\mu; 0, \epsilon I) \quad (2)
\]

\[
p(x|\mu) = N(x; \mu, \sigma I), \quad (3)
\]

where \( \mu \) and \( x \) represent the speaker mean and speaker vector, respectively; \( \epsilon \) and \( \sigma \) are the between-speaker variance and the within-speaker variance, respectively.

With this model, it is easy to derive the marginal probability \( p(x) \) and the posterior probability \( p(\mu|x) \) based on the Bayes rule \([24]\). Similarly, the likelihood \( p_k(x) \) can be computed by marginalizing over \( \mu_k \), where \( \mu_k \) can be estimated from the enrollment samples \( \{x_1^k, ..., x_n^k\} \):

\[
p_k(x) = p(x|x_1^k, ..., x_n^k) = \int p(x|\mu_k)p(\mu_k|x_1^k, ..., x_n^k)d\mu_k = N(x; \frac{n_k\epsilon}{n_k\epsilon+\sigma}x_k, (\sigma + \frac{\epsilon\sigma}{n_k\epsilon+\sigma})I). \quad (4)
\]

Finally, a logarithmic NL form can be computed as:

\[
\log NL(x|k) = \log p_k(x) - \log p(x) \quad (5)
\]

\[
\propto -\frac{1}{\sigma} + \frac{\epsilon\sigma}{n_k\epsilon+\sigma}|x - \hat{\mu_k}|^2 + \frac{1}{\epsilon + \sigma}|x|^2.
\]

### 4.2. Three-phase perspective

A simple arrangement on the NL score shows that:

\[
NL = \frac{p(x|x_1, ..., x_n)}{p(x)} = \frac{\int p(x|\mu)p(\mu|x_1, ..., x_n)d\mu}{p(x)} \quad (6).
\]

By this NL form, the score is computed based on three phases:

- The enrollment phase \( p(\mu|x_1, ..., x_n) \) that produces the posterior of the class mean \( \mu \).
- The prediction phase \( p(x|\mu) \) that computes the probability of a test sample belonging to a class represented by the class mean \( \mu \).
- The normalization phase \( p(x) \) that computes the probability that \( x \) is produced by all potential classes.

Usually, these three phases are based on the same statistical model, under the assumption that the statistics of enrollment and test conditions are the same. In this case, the NL score is mathematically equal to PLDA \([24]\). In conditions where the enrollment and test are in different domains, the statistics of enrollment and test conditions are different, and so the three phases should use different statistics, in order to obtain an optimal score. This phenomenon is called statistics coherence (between scoring phases).

The concept of three-phase scoring provides a clear explanation of the strange behavior we observed in Section 4.3. Decoupled scoring

Following the three-phase perspective, a principle solution to domain mismatch is to use the respective statistical model for each phase, which we call domain statistics decomposition (DSD). Firstly, for the enrollment phase, the statistical model of the enrollment condition \( \{\epsilon I, \sigma I\} \) should be used. Secondly, for the normalization phase, the statistical model of the test condition \( \{I, \sigma I\} \) should be used. Finally, for the prediction phase, a transform is applied to connect the conditional probability \( p(x|\mu) \) and the posterior \( p(\mu|x_1, ..., x_n) \). For simplicity, we assume this transform is linear:

\[
x = \hat{x}M + b, \quad (7)
\]

where \( \hat{x} \) represents the observation in the test condition, and \( x \) is the transformed data in the enrollment condition. Obviously, if the transformed data can be well represented by the statistical model of the enrollment condition, the optimal NL score can be derived.

According to Eq.\([4]\) and Eq.\([7]\), we can obtain the prediction probability based on the model of the enrollment condition:

\[
p_k(\hat{x}; M, b) = \frac{p(M\hat{x} + b|x_1^k, ..., x_n^k)}{p(x)} = \int p(M\hat{x} + b|\mu_k)p(\mu_k|x_1^k, ..., x_n^k)d\mu_k = N(M\hat{x} + b, \frac{n_k\epsilon}{n_k\epsilon+\sigma}x_k, (\sigma + \frac{\epsilon\sigma}{n_k\epsilon+\sigma})I). \quad (8)
\]

According to Eq.\([5]\), the NL score is then computed as follows:

\[1\]For the prediction phase, there is no between-class distribution required; and for the normalization phase, we need a between-class distribution that matches the within-class distribution in order to represent the marginal distribution of the test data.
The optimal parameters $\{M, b\}$ can be estimated by maximum likelihood (ML) training. The objective function for this optimization can be written by:

$$\mathcal{L}(M, b) = \sum_{k=1}^{K} \sum_{i=1}^{N} p_k(\hat{x}_i; M, b),$$  \hspace{1cm} (10)

where $K$ denotes the number of speakers, and $N$ denotes the number of test samples in each speaker. In our experiment, the Adam optimizer [25] was used to optimize $\{M, b\}$.

5. EXPERIMENTAL RESULTS

In our experiments, the conventional MDT/DAT and our proposed DSD methods are implemented to deal with domain mismatch problem.

5.1. Basic results

The basic result with three methods are reported in Table 2. It can be observed that the proposed DSD method consistently outperforms MDT and DAT, demonstrating that DSD is more effective in dealing with domain mismatch. The comparison between DSD and DAT is especially interesting, as the two methods look very similar and only differ in the normalization term $p(x)$. The clear advantage of DSD demonstrated the solid theory of this decoupled scoring approach.

| Cases  | Base | MDT | DAT | DSD |
|--------|------|-----|-----|-----|
| AND-AND | 0.797 | -   | -   | -   |
| AND-Mic | 2.146 | 1.151 | 1.245 | 0.981 |
| AND-iOS | 1.425 | 1.161 | 1.512 | 0.623 |
| Mic-AND | 2.175 | 1.161 | 1.189 | 0.712 |
| Mic-Mic | 0.778 | -   | -   | -   |
| Mic-iOS | 2.251 | 1.293 | 1.481 | 0.812 |
| iOS-AND | 1.599 | 1.156 | 1.184 | 0.755 |
| iOS-Mic | 2.216 | 1.137 | 1.231 | 1.052 |
| iOS-iOS | 0.920 | -   | -   | -   |

5.2. Further analysis

To better understand the capability among three methods to squeeze the value of cross-domain labels, different number of speakers are sampled from AIShell-1.Dev to train MDT, DAT and DSD respectively. Results are reported in Table 3.

| Methods | Cases | # of speakers |
|---------|-------|---------------|
|         |       | 68  | 136  | 204  | 272  | 340  |
| MDT     | Mic-AND | 5.093 | 1.896 | 1.264 | 1.287 | 1.245 |
|         | Mic-iOS | 5.185 | 1.628 | 1.250 | 1.250 | 1.161 |
| DAT     | Mic-AND | 5.586 | 2.284 | 1.274 | 1.194 | 1.189 |
|         | Mic-iOS | 5.732 | 2.213 | 1.491 | 1.420 | 1.293 |
| DSD     | Mic-AND | 5.213 | 1.807 | 1.236 | 1.151 | 1.156 |
|         | Mic-Mic | 5.296 | 1.900 | 1.165 | 1.165 | 1.236 |

6. CONCLUSIONS

This paper investigated the issue of domain mismatch in speaker verification task, and found that the statistics incoherence was the essential problem associated with this mismatch. To deal with this problem, we presented a decoupled scoring approach. Specifically, we decoupled the scoring process to three phases according to the normalized likelihood (NL) framework, and used the respective statistical model for each phase. A simple yet effective linear transform was applied to implement this approach. Experimental results demonstrated that the proposed decoupled scoring approach was highly effective to squeeze the value of cross-domain data and obtained the best performance compared to other competitive methods. Future work will extend this approach to many other mismatch scenarios, e.g., dynamic speaker enrollment, multi-genre test.
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