Back-ends Selection for Deep Speaker Embeddings

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Abstract

Probabilistic Linear Discriminant Analysis (PLDA) was the dominant and necessary back-end for early speaker recognition approaches, like i-vector and x-vector. However, with the development of neural networks and margin-based loss functions, we can obtain deep speaker embeddings (DSEs), which have advantages of increased inter-class separation and smaller intra-class variance. In this case, PLDA seems unnecessary or even counterproductive for the discriminative embeddings, and cosine similarity scoring (Cos) achieves better performance than PLDA in some situations. Motivated by this, in this paper, we systematically explore how to select back-ends (Cos or PLDA) for deep speaker embeddings to achieve better performance in different situations. By analyzing PLDA and the properties of DSEs extracted from models with different numbers of segment-level layers, we make the conjecture that Cos is better in same-domain situations and PLDA is better in cross-domain situations. We conduct experiments on VoxCeleb and NIST SRE datasets in four application situations, single-/multi-domain training and same-/cross-domain test, to validate our conjecture. In addition, we briefly conduct some validation and discussion on domain adaption algorithms.

Index Terms: speaker verification, PLDA, Cosine similarity scoring, domain adaption

1. Introduction

Speaker recognition aims to verify the identities of speakers from samples of their voices, which has been deployed in many commercial products successfully. In the early years, i-vector [1] front-end and PLDA [2,3] back-end are the dominant model since they are proposed. With the rise of neural networks, discriminatively trained DNNs or CNNs [4,7] surpass i-vector as the state-of-the-art front-ends. Extensive work focuses on improving discrimination of front-ends, developing more comprehensive neural architectures [8,9], improving pooling methods etc. There, we wonder whether the number of segment-level layers affects back-ends selection.

Finally, we conduct experiments on VoxCeleb and NIST SRE datasets in four application situations, single-/multi-domain training and same-/cross-domain test. Our experiments results validate our conjecture. In addition, we briefly conduct some validation and discussion on domain adaption algorithms.

2. PLDA and Deep Speaker Embeddings

2.1. PLDA

2.1.1. Revisiting PLDA

Assume there exists a matrix $A^{-T}$ which diagonalizes both the covariance matrix of the between-class distribution $\Phi_u$ and the shared covariance matrix of the within-class distributions $\Phi_v$ of individual classes to $\Psi$ and $I$, i.e.

$U^T\Phi_uU = \Psi$ and $U^T\Phi_vU = I$. Then, the simplified model is written as:

$x = m + Au \text{ where } u \sim N(\mu, \Sigma) \text{ and } v \sim N(0, \Psi) \text{ (2)}$

where $x$ represents examples, i.e. speaker embedding; $u$ represents the class center; $\mu$ represents an example of that class in the projected space. Members of the same class share the class variable $u$, and the class-conditional distributions have a common covariance matrix $\Sigma$.
2.1.2. PLDA log-likelihood ratio

Given two speaker embeddings, \( x_1 \) and \( x_2 \), PLDA provides the log-likelihood ratio between the same-speaker and different-speaker hypotheses, \( H_1 \) and \( H_0 \). The PLDA LLR is given by:

\[
LLR(x_1, x_2) = \log\left(\frac{p(x_1, x_2|H_1)}{p(x_1, x_2|H_0)}\right)
\]  

(3)

According to Eq(2), embedding, i.e., \( x \), is preprocessed by:

\[
u = A^{-1}(x - m)
\]

(4)

Then, given the \( \Psi \) and \( I \) are diagonal matrix, the PLDA LLR can be expressed entirely in terms of scalar operations:

\[
LLR(x_1, x_2) = \log \left( \frac{\int \mathcal{N}(u_1; v, I)\mathcal{N}(u_2; v, I)\mathcal{N}(v; 0, \Psi)dv}{\mathcal{N}(u_1; 0, \Psi + I)\mathcal{N}(u_2; 0, \Psi + I)} \right)
\]

\[
= \frac{1}{2} \sum_{i=1}^{D} \left\{ c_i + m_i(u_{1,i}u_{2,i} - \psi_i(u_{1,i} - u_{2,i}))^2 \right\}
\]

(5)

where: \( c_i = -\log(2\psi_i + 1)^2 \), \( m_i = \frac{\psi_i}{(2\psi_i + 1)(\psi_i + 1)} \)

\[
\cos(x_1, x_2) = \sum_{i=1}^{D} x_{1,i}x_{2,i}
\]

(6)

By referring to the derivations, it is easy to find that PLDA LLR can be expressed as a weighted sum of weighted Cos similarity and Euclidean distance, which considers test data similarity and the distribution of the training data.

In same-domain situations, it is clear that larger \( \psi_i \) is better because larger \( \psi_i \) means a lower score when speakers are different by deriving expectations for each dimension in Eq(7). Furthermore, due to \( u \sim \mathcal{N}(v, I) \) and \( v \sim \mathcal{N}(0, \Psi) \), it is obvious that the larger the value of \( \Psi \), the better the PLDA discriminative capacity since within-class distribution is the identity matrix.

\[
E\left\{ \frac{\psi_i}{2(\psi_i + 1)}(u_{1,i}u_{2,i} - \psi_i(u_{1,i} - u_{2,i}))^2 \right\}
\]

\[
= \begin{cases} 
\psi_i \left( \frac{(2\psi_i + 1)\psi_i}{(2\psi_i + 1)(\psi_i + 1)} \right) & \text{when } H_1 \\
2 - \psi_i^2 & \text{when } H_0
\end{cases}
\]

(7)

In cross-domain situations, according to Eq(5), i) the larger the testing data \( (u, i) \) variance, the better the discrimination, ii) the greater \( \psi_i \), the heavier weight of the dimension in the score, iii) due to test data variance and PLDA variance are usually close, larger PLDA variance means more minor deviation, which is, more robust, because \( m_i \) in Eq(5) is positively correlated with \( 1/\psi_i \) if \( \psi_i > 1 \). Thus, PLDA may be more robust than Cos in cross-domain situations.

The PLDA parameters \( \mu, A, \Psi \) in the PLDA formula are optimal solutions in the training data space, thus, performance degradation is inevitable when encountering cross-domain problems unless the bias is the same in each dimension.

Here, one thing deserves to be stated. Compared to Cos, two major differences of PLDA are the underlying Gaussian assumption and usage of the training data distribution. Simple Gaussian assumptions of PLDA lead to desirable generalization but also limit the performance of DSEs. Utilizing the training data distribution improves the robustness but inevitably leads to performance degradation when encountering domain mismatch.

2.2. Deep speaker embeddings

As analyzed in the prior subsection, the distribution of embeddings has an influence on PLDA. Thus, we analyze the distribution of DSEs extracted from models with different (one or two) numbers of fully-connected layers in the segment-level part.

For convenience, embeddings extracted from the model with one fc layer are denoted as 1fc embeddings, embeddings extracted from the first fc layer, away from the classification layer, are denoted as 2fc-1 embeddings, the second layer is denoted as 2fc-2 embeddings. As shown in Fig(1) the distribution of 2fc-2 embeddings and 1fc embeddings are similar and are quite different from 2fc-1 embeddings, but they all have strong discrimination. Due to the compact distribution of 2fc-1 embeddings, there is a significant overlap between intra- and inter-class distances. While no overlap exists for 1fc/2fc-2 embeddings due to the strong constraints of loss function, indicating the latter is better for Cos. Since there is just a simple non-linear relationship between 2fc-1 embeddings and 2fc-2 embeddings, 2fc-1 embeddings have a stronger speaker discrimination potential.

2.3. Back-ends selection for different situations

Based on the analysis of the previous two subsections, we analyze the back-ends selection in different situations.
For the same-domain situations, since distributions are similar, the strong discrimination on the training set works perfectly on the test set, no matter what distribution they are. While the non-Gaussian distribution of DSes causes great difficulty for PLDA and leads to a performance decrease. Study [22] shows that the contribution of PLDA for deep speaker embeddings is regularization rather than discrimination, that is, PLDA tends to discover some underlying speech codes that are intrinsically Gaussian and comparable across speakers. Although these codes may be more generalized, they are more likely to result in performance degradation on same-domain test. Thus, one conjecture can be made that 1fc/2fc-2+Cos gets better performance in same-domain situations.

For the cross-domain situations, the strong discrimination of DSes on the training set is not robust or even harmful, so the performance of Cos is usually poor. The more diverse the training set, the better the performance of Cos. Compared to Cos, there are two advantages of PLDA. Firstly, the PLDA projected space constructed based on Gaussian assumptions is more generalizable. Secondly, more discriminative dimensions in the space are more robust to cross-domain. An important measure of cross-domain is whether the test data variance deviates from the training data in the PLDA projected space. Usually, the trend in variance with dimensions is similar for most domain data. Sec4.4 will present it in detail. Then, dimensions with larger PLDA variance, i.e. more discriminative, are more insensitive to variance variability between PLDA and test data to be more robust to cross-domain data. Therefore, the other conjecture can be made that 2fc-1+PLDA has a better performance in cross-domain situations.

3. Experiments Setting

We conduct experiments on four conditions, single/multi-domain training and same/cross-domain test. Model training is conducted on three training sets, (a) the VoxCeleb2 [34,35] dev part, which contains speech from 5994 speakers. The experiments settings are same as [16]. No speech augmentation and voice activity detection (VAD) are used in the series of experiments. (b) NIST SRE CTS superset (CTS) [36], contains 6867 speakers. 81-dimensions fbanks spanning the frequency range 40-3800Hz are used and 3-dimensions pitch features are concatenated. All data are augmented by convolving with far-field Room Impulse Responses (RIRs) and adding noise from the MUSAN corpus. An energy-based and harmonics-based VAD is used to drop the non-speech frames. (c) CTS and Vox2Cat, which contain a total of 12861 speakers. Due to the short duration of speech from VoxCeleb2, we concatenate the subsegments belonging to the same original video into a unique segment, named as Vox2Cat. All audios are converted to 8kHz-16bit-PCM in WAV format files. Speech augmentation and VAD are the same as (b).

We evaluate our models on two series of sets, (i) Vox1-O/H, (ii) SRE21-dev&eval. The former test sets are well known, and we briefly introduce the latter, SRE21-dev&eval. Compared to the prior SREs, the key challenges of SRE21 are multi-channel and multi-language speaker recognition based on audio-from-video and telephone speech segments, which cause extremely serious enrollment-test and training-test cross-domain problems. The SRE21 sets we used in all experiments are preprocessed by codec and denoiser.

We conduct the experiments on two models, ResNet34 and ETDNN. ASP layer and circle loss [16] are used in all models. All models are trained with stochastic gradient descent and random chunk size. (a) models interval is set to [200,400],[300-500] and [400,600]. (b) and (c) models interval is set to [400,800],[600-1000], [800-1000/1200] in three training stages. The performance on the Vox series test set is gauged in terms of the EER, minDCF with $\pi_{target} = 0.01$, and the NIST SRE21 sets are gauged with EER and minimum $C_{primary}$, which are calculated with the default scripts [30].

4. Results and Analysis

In this section, we explore how to select back-ends in various situations by experiments, noting that Cos of 2fc uses 2fc-2 embeddings, PLDA uses 2fc-1 embeddings in all Table.

4.1. single-domain training, same-domain test

We conduct the same-domain experiments on the VoxCeleb sets with ResNet34 and ETDNN with 512 channels.

Table 1: Results of Vox test sets when training data is Vox2

|                | Vox1-O EER | Vox1-O minDCF | Vox1-H EER | Vox1-H minDCF |
|----------------|------------|---------------|------------|---------------|
| ResNet34       |            |               |            |               |
| Cos 1fc PLDA   | 1.19       | 0.159         | 2.46       | 0.229         |
| Cos 2fc PLDA   | 1.39       | 0.115         | \textbf{2.56} | \textbf{0.237} |
| ETDNN          |            |               |            |               |
| Cos 1fc PLDA   | 1.92       | 0.191         | 3.28       | 0.287         |
| Cos 2fc PLDA   | 1.45       | 0.182         | 2.67       | 0.260         |

As shown in Table 1 three things can be observed: i) severe performance degradation is caused by adopting PLDA scoring on 1fc embeddings, compared to Cos, ii) PLDA scoring of 2fc-1 embeddings is slightly better than Cos of 2fc-2 embeddings, iii) the performance of Cos using 1fc embeddings is better than the performance of PLDA scoring using 2fc-1 embeddings.

Thus, one rough conclusion can be drawn, in single-domain training, same-domain test conditions, the performance of Cos is better than PLDA. Considering simplicity and performance, Cos is a better choice. These things prove our analysis and conjectures. The reason why the performance of Cos of 2fc-2 embeddings is worse than 1fc is information loss caused by ReLU activation functions. Using other activation functions partly alleviates degradation and gets better Cos performance but slightly damages PLDA scoring of 2fc-1 embeddings.

4.2. Single-domain training, cross-domain test

we conduct experiments on the CTS with ResNet34 and ETDNN with 1024 channels. Models are evaluated on SRE21 dev&eval. Results are shown in Table 1 and no adaption is applied. Some different things happen compared to Sec4.1.

Firstly, PLDA scoring is significantly better than Cos in all conditions, about 4%-15% in 1fc and about 15%-30% in 2fc-1 in term of min($C_p$). A larger improvement of PLDA in 2fc-1 further proves our conjecture in Sec4.1. Secondly, although Cos

The performance of Cos using 2fc-1 embeddings is unacceptable due to its compact distribution, and we do not present it. Also, since the distribution and PLDA scoring of 2fc-1 embeddings is similar to 1fc embeddings, we also overlook it.
Table 3: Results of SRE21&Vox test sets when training data is CTS and Vox2Cat

|                | sre21-dev | sre21-eval | vox1-O | Vox1-H |
|----------------|-----------|------------|--------|--------|
|                | EER minCp | EER minCp  | EER    | mindcf |
| ResNet34       |           |            |        |        |
| 1fc Cos        | 8.39      | 0.589      | 8.47   | 0.506  |
| CTS-PLDA       | 7.40      | 0.634      | 8.29   | 0.632  |
| 2fc Cos        | 9.76      | 0.585      | 8.88   | 0.497  |
| CTS-PLDA       | 6.15      | 0.395      | 6.57   | 0.382  |
| ETDNN          |           |            |        |        |
| 1fc Cos        | 7.98      | 0.488      | 7.48   | 0.481  |
| CTS-PLDA       | 7.49      | 0.537      | 7.77   | 0.547  |
| 2fc Cos        | 8.49      | 0.563      | 8.19   | 0.505  |
| CTS-PLDA       | 7.05      | 0.445      | 7.37   | 0.502  |

Table 2: Results of SRE21 sets when training data is CTS

|                | SRE21-dev | SRE21-eval | SRE21-dev | SRE21-eval |
|----------------|-----------|------------|-----------|------------|
|                | EER       | minCp      | EER       | minCp      |
| ResNet34       |           |            |           |            |
| 1fc Cos        | 9.94      | 0.644      | 9.74     | 0.548      |
| PLDA           | 6.87      | 0.446      | 6.76     | 0.471      |
| 2fc Cos        | 13.27     | 0.719      | 12.27    | 0.621      |
| PLDA           | 6.58      | 0.423      | 6.97     | 0.434      |
| ETDNN          |           |            |           |            |
| 1fc Cos        | 10.00     | 0.586      | 9.65     | 0.553      |
| PLDA           | 9.26      | 0.576      | 8.59     | 0.532      |
| 2fc Cos        | 9.90      | 0.586      | 9.60     | 0.548      |
| PLDA           | 10.09     | 0.468      | 8.86     | 0.474      |

4.3. Multi-domain training

Results are presented in Table 3. PLDA for Vox sets is trained by Vox2 while that for SRE21 is trained by CTS. Three things worth noting: i) Although 2fc-1+PLDA is still the best in cross-domain situations, the improvements by PLDA is fewer than Sec4.2, and the performance of Cos using 1fc embeddings is better than Sec4.2. ii) Different from Sec4.2, slight performance degradation is caused by PLDA for 1fc, and even get worse results than Sec4.2. iii) PLDA causes universal performance degradation in the same-domain test, either in 1fc or 2fc. Thus far, we conclude that Cos with 1fc is better in same-domain situations and PLDA with 2fc-1 is better in cross-domain situations.

4.4. Domain adaption analysis

As discussed in Sec2.1, differences between PLDA variance and test data variance reflects the domain mismatch. As seen in Fig 3(a)&(b), the variance of Vox1 sets and Vox2 training data are approximately consistent, while SRE21 sets and CTS training sets are quite different, especially at lower variance. The standard deviation is used in Fig 3 to enlarge differences. Thus, the main role of back-ends adaption methods is to align training-test statistics, mean and variance. The CORAL algorithm [37], which is simple, focus on aligning the covariance between different domain embeddings by whitening and re-colouring. They can be equivalently applied to back-ends since operations are linear. A major issue of the CORAL algorithm is that it is overconfidence in in-domain data distribution, especially with limited in-domain data. Considering these, the CORAL+ algorithm introduces interpolation and regularize. Since larger PLDA variance means less deviation, as analyzed in Sec2.1. Thus, one max() operator is introduced in the CORAL+ algorithm [38]. Fig3(c)&(d) shows the variance after CORAL and CORAL+. It is found that the lower variances are aligned by CORAL+, while CORAL does not work. PLDA results after adaption are displayed in Table 4. The CORAL+ achieve about 15%-20% improvements on minCp.

5. Conclusions

The paper systematically explores back-ends selection for DSEs in different situations by theory analysis and experiments validation. By analyzing PLDA and the properties of DSEs, we conjecture that Cos is better in same-domain situations and PLDA is better in cross-domain situations. Then, we validate our conjecture by conducting experiments on VoxCeleb and CTS. Differences between the variances of PLDA and test data cause performance degradation in cross-domain situations.
6. References

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