Weakly Supervised PLDA Training

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Abstract

PLDA is a popular normalization approach for the i-vector model, and it has delivered state-of-the-art performance in speaker verification. However, PLDA training requires a large amount of labelled development data, which is highly expensive in most cases. We present a cheap PLDA training approach, which assumes that speakers in the same session can be easily separated, and speakers in different sessions are simply different. This results in 'weak labels' which are not fully accurate but cheap, leading to a weak PLDA training.

Our experimental results on real-life large-scale telephony customer service achieves demonstrated that the weak training can offer good performance when human-labelled data are limited. More interestingly, the weak training can be employed as a discriminative adaptation approach, which is more efficient than the prevailing unsupervised method when human-labelled data are insufficient.

Keywords: PLDA; I-vector,; Unsupervised learning; Speaker verification

1 Introduction

The i-vector model plus various normalization approaches offers the standard framework for modern speaker verification [1, 2, 3, 4]. Basically, the i-vector model uses a Gaussian mixture model (GMM) or a deep neural network (DNN) to collect the Baum-Welch statistics, based on which an affine transform is learned so that speech segments can be projected onto low-dimensional continuous vectors (i-vectors). Although it is possible to discriminate speaker i-vectors using simple cosine distance, normalization or discriminative techniques are often preferred, since they promote speaker-related information and thus bring significant performance improvement. Probabilistic linear discriminant analysis (PLDA) is one of the most popular normalization methods. It assumes that i-vectors of a particular speaker subject to a Gaussian distribution, with the mean vector following a normal distribution [2]. Combined with length normalization, PLDA has delivered state-of-the-art performance in various test benchmarks [4].

PLDA Training generally requires a large amount of human-labelled data, usually thousands of speakers, each with multiple sessions. For example, in the two popular development databases Fisher [5] and Switchboard [6], there are $12,399$ and 543 speakers, respectively. In practice, labelling such a large amount of data by human is very challenging: it is not only because discriminating two voice-similar speakers is difficult, but also because identifying the speaker of an utterance among thousands of people is nearly impossible. Therefore, it is quite appealing if the data can be utilized directly without human labeling.

A popular approach towards this direction is various unsupervised adaptation techniques. For example, Wang et al. [7] proposed a domain-adaptation approach based on maximum likelihood linear transformation (MLLT), and Rahman et al. [8] proposed a dataset-invariant covariance normalization approach that normalized i-vectors by a global covariance matrix computed from both in-domain and out-domain data. This is equal to project i-vectors of in-domain and out-domain speakers onto a dataset-invariant space, so that the PLDA model trained with the projected i-vectors is more robust against data mismatch.

Another approach to utilizing unlabelled data is to produce labels for these data automatically. These labels may be not as accurate as human labels but still convey some speaker-related information, and therefore can be used as supplemental materials in PLDA training. Most importantly, these labels are very cheap, allowing vast unlabelled data to be used. We call these cheap labels 'weak labels', and the PLDA training based on these labels 'weak training'. Correspondingly, the PLDA training with human labels is called 'strong training'.

Some research has been conducted on weak PLDA training. Garcia-Romero et al. [9] proposed a semi-supervised learning approach that used an out-of-domain PLDA to cluster in-domain data, based on which the PLDA projection matrix was adapted. Villalba and colleagues [10] proposed a variational Bayesian method where the unknown label of an unlabelled utterance was treated as a latent variable. This can be seen as an extension of the semi-supervised method. Liu et al. [11] proposed an approach that treated unlabelled data as from a special universal speaker, and the PLDA was trained with the universal speaker involved.

This paper proposes a new knowledge-based weak PLDA training approach that produces cheap labels based on some prior knowledge. For example, in the telephony customer service domain, the prior knowledge is that speakers in different sessions are almost different, and therefore the session ID can be used to label speakers. These labels are certainly noisy (therefore weak) since the knowledge is not absolutely correct, but they do convey some valuable information that can be used to enhance PLDA. Our experiments on a real-life large-scale customer service archive demonstrated that the knowledge-based weak training is rather effective in domains where the knowledge is 'sufficiently correct' and can provide performance improvement, and even outperform the unsupervised adaptation approach in scenarios when human-labelled data are limited.

The structure of this paper is as follows: Section 2 presents details of weak training, and Section 3 presents the experiments. Finally Section 4 concludes the paper and discusses some future work.

2 Knowledge-based weak PLDA training

In this section, the conventional PLDA model is briefly reviewed, and then our proposed knowledge-based weak training approach is presented. We also discuss the relation of our proposal methods and some others.

2.1 PLDA model

PLDA is an extension of the linear discriminative analysis (LDA), by introducing a Gaussian prior on the mean i-vector of each speaker. Combined with length normalization, PLDA has delivered state-of-the-art performance in speaker verification.

Letting w_{ij} denote the i-vector of the jth utterance (session) of the ith speaker, the PLDA model can be formulated as follows:

$$w_{ij} = u + V y_i + z_{ij},$$

where u is the speaker-independent global factor, y_i and z_{ij} represent the speaker-level and utterance-level factors, respectively. The matrix V consists of the basis of the speaker subspace. Note that both y_i and z_{ij} are assumed to follow a diagonal full-rank Gaussian prior. The model can be trained via an EM algorithm [12], and the similarity of two i-vectors can be computed as the ratio of the evidence (likelihood) of two hypothesises: whether or not the two i-vectors belong to the same speaker [13].

2.2 Knowledge-based weak training

Figure 1 Illustration of the difference between human labels and weak labels.
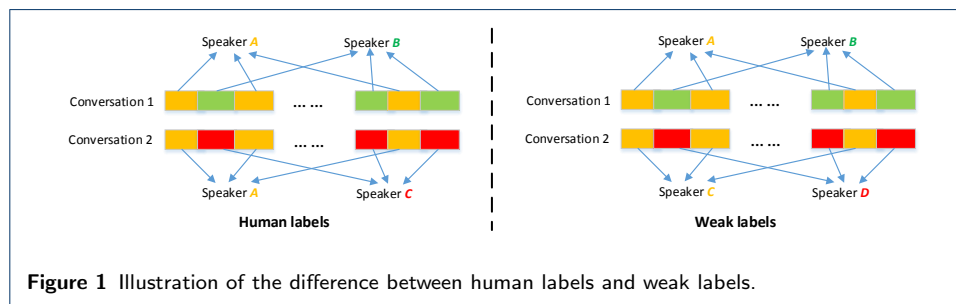
We propose a weak training approach that relies on some prior knowledge to get cheap labels for unlabelled data. For example in the customer service domain that the paper focuses on, we utilize two pieces of prior knowledge: (1) there are only a few (often two) participants in a single session, and they can be easily separated; (2) the speakers in different sessions are probably different, especially for customers. By these knowledge, an utterance can be simply assigned a label that involves a session ID and a local speaker ID, i.e., an ID is valid only within the session. These labels are not fully correct (so are weak labels), but in most cases they are.

Fig. 1 illustrates the difference between human labels and the weak labels derived from the above prior knowledge, where each speaker is represented by a particular color. For human labels, the segments from the same speaker but different sessions are correctly labelled. For weak labels, speakers in different sessions are labelled as different, even if they are actually the same. Once the weak labels are generated, the PLDA training is conducted as usual as with human labels.

2.3 Relation to other methods

The knowledge-based weak training proposed here is related to the semi-supervised PLDA training in [9]. Both of them rely on weak and cheap labels, but the labels are produced in different ways: the knowledge-based weak training relies on domain-specific prior knowledge, and the performance is determined by the correctness of the knowledge; the semi-supervised training relies on the the existing PLDA model,

and the performance is determined by the quality of the existing model. From this perspective, the semi-supervised training can be regarded as a model-based weak training. We argue that the knowledge-based weak training is superior in scenarios where human-labelled data are insufficient that a strong primary PLDA is not available.

The knowledge-based weak training is also related to unsupervised PLDA adaptation [9, 10, 11, 7, 8]. Both the two methods make use of the distribution information of unlabelled data and thus can be employed to perform model adaptation. The difference is that the weak training also utilizes speaker-discriminant information, which, although noisy, is still beneficial if the knowledge is mostly correct. We therefore conjecture that the knowledge-based weak training is more effective than unsupervised adaptation in scenarios where the discriminative information is desirable.

3 Experiment

The proposed weak training approach is tested on a practical speaker verification system trained with a large-scale telephony customer service archive. The system is implemented based on the GMM-ivector framework. We first present the data profile and then report the results.

3.1 Data and configurations

The training data used to train the GMM-ivector system are composed of 500 hours of conversational speech signals sampled from a large-scale telephony customer service archive. These data are used to train the UBMs and the T matrix of the i-vector model. The development data used to train the PLDA model are divided into two data sets: the STRONG set and the WEAK set that are labelled by human and the prior knowledge described in the previous section, respectively. Note that, the acoustic condition of the WEAK set is more close to that of the evaluation data, which means that the WEAK set can be regarded as in-domain and therefore any improvement with this set could be partially due to model adaptation.

The STRONG set involves speech signals of $2,000$ speakers, and the WEAK set consists of $2,000$ double-channel sessions, each with two speakers. Each session consists of a customer channel and a service channel, and the two channels are separated physically. The WEAK set of the customer channel forms a WEAK-customer subset and the WEAK set of the service channel forms a WEAK-service subset. We distinguish customer data and service data because they hold very different properties, particularly the probability that the 'different session, different speaker' assumption holds. Finally, we sample $1,000$ sessions from WEAK-customer and $1,000$ sessions from WEAK-service, composing a WEAK-mix subset. More details about the development data are shown in Table 1.

The evaluation set involves $1,236$ speakers and the enrollment speech for each speaker is 30 seconds in length. The length of the test utterances is 15 seconds and each speaker contains about 6 test utterances. By pair-wised composition, $9,469,462$ trails are constructed, including $7,649$ target trials and $9,461,813$ imposter trails.

The acoustic feature used in our experiments is the 60-dimensional Mel frequency cepstral coefficients (MFCCs), which involves 20-dimensional static components

Table 1 Development set for PLDA training.

	# of Spks/Sessions	# of Utts
STRONG	2,000	15,718
WEAK-customer	2,000	21,463
WEAK-service	2,000	25,852
WEAK-mix	2,000	23,987

plus the first and second order derivatives. The frame size is 20 ms and the frame shift is 10 ms. The UBM involves $1,024$ Gaussian components and the dimensionality of the i-vector space is 400. The performance is evaluated in terms of Equal Error Rate (EER) [14].
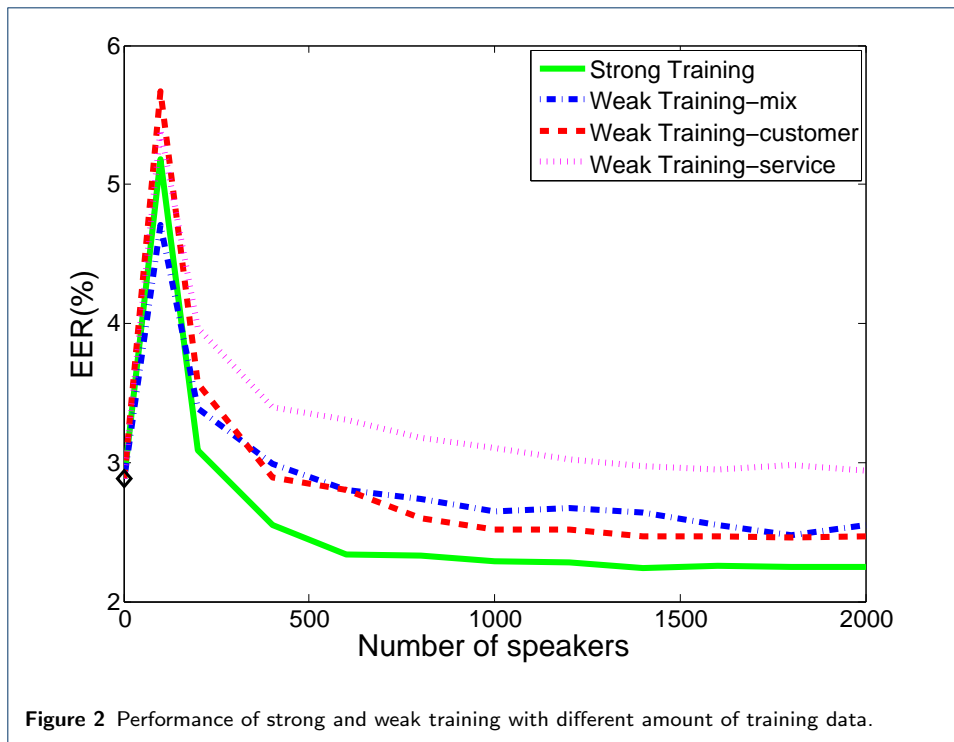
3.2 Strong and weak training
The first experiment studies the performance of the knowledge-based weak PLDA training, and compare it with the strong training that uses the human-labelled data. The EER results are shown in Table 2, where the results with the STRONG set and three WEAK subsets are reported. For comparison, the results with cosine scoring (NO PLDA) are also presented. We first observe that most of the PLDA models outperform the cosine scoring. This is particular interesting for the weak training approach, where only inaccurate labels are used. This confirms our conjecture that it is possible to use weak labels derived from prior knowledge to train PLDA, at least in scenarios where the prior knowledge is correct.

Table 2 EER(%) results of strong and weak training.

Scoring Method	EER%
Cosine	2.88
PLDA: STRONG	2.25
PLDA: WEAK-customer	2.47
PLDA: WEAK-service	2.94
PLDA: WEAK-mix	2.55

Comparing the results with the three WEAK subsets, it can be observed that WEAK-customer delivers the best performance, while WEAK-service shows the worst (the performance is actually worse than with Cosine scoring). This is also understandable, since the number of service people is limited (about 200) so speaker labels of the $2,000$ sessions of the WEAK-service subset are probably incorrect (sessions of the same speaker are labelled as distinct speaker IDs). In contrast, the probability that two customers appear in the $2,000$ sessions in WEAK-customer is fairly low, which means a perfect match between the prior knowledge and the real data, leads to the good performance.
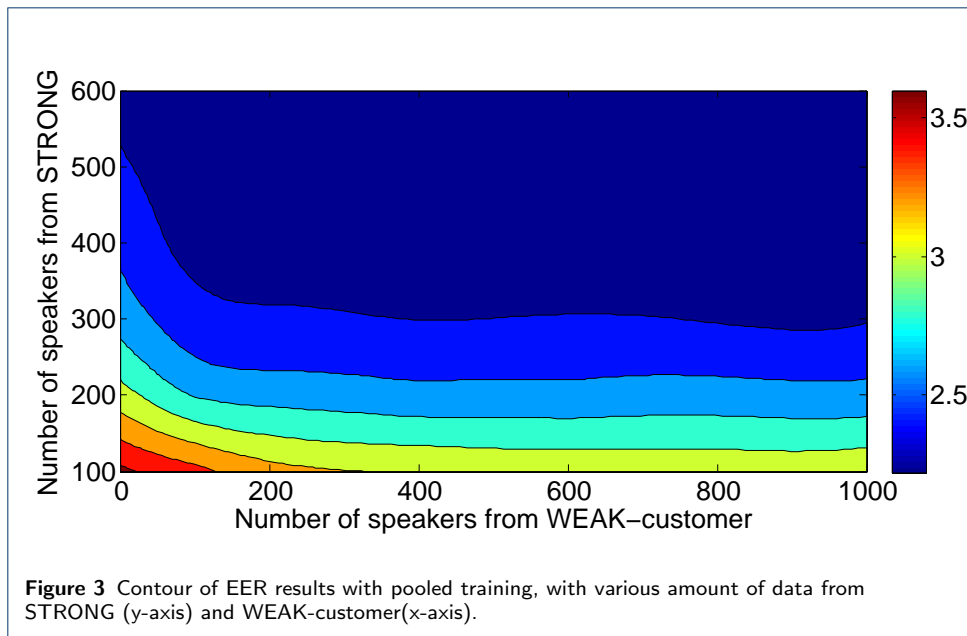
In the second experiment, we investigate the performance of different PLDA training methods with various amount of training data. The results are shown in Fig. 2, where the data volume is controlled by the number of speakers. The diamond at the starting point of each curve represents the performance with the cosine scoring. It can be seen that with limited data (less than 200), the PLDA models, despite strong training or weak training applied, do not provide better performance than

Figure 2 Performance of strong and weak training with different amount of training data.

the simple cosine scoring. With more data, the PLDA models offer better performance than the cosine baseline. The strong training is superior to the weak training, and for the weak training, the model trained with WEAK-customer shows better performance than with WEAK-service, due to the reason that has been discussed already.

3.3 Pooled training

In this experiment, we assume limited human-labelled data and use weakly labelled data to enhance the PLDA model. More precisely, the weakly-labelled data are augmented with the human-labelled data to train the PLDA, which we call 'pooled training'. According to the experience in the last experiment, only the data in WEAK-customer are used for data augmentation. Fig. 3 shows the contour of the performance of the pooled training, with various amount of data from STRONG and WEAK-customer. It can be seen that if the human-labelled data are limited (the number of speakers is less than 500), augmenting weakly-labelled data offers clear performance improvement, and the more data augmented, the more performance improved. However, the effectiveness of the augmentation is not unlimited: the additional contribution becomes marginal if the amount of weakly-labelled data is more than 800 speakers. This is not surprising considering the noise involved in the data. Fig. 3 also suggests an interesting concept of 'substitution amount', i.e., how many weakly-labelled data can substitute for a certain amount of human-labelled data. The contour in Fig. 3 indicates that the more human-labelled data are provided, the more difficult they can be substituted by weakly-labelled data. In other words, the most value of human-labelled data is to provide additional performance gains, instead of offering baseline performance. This suggests an active learning approach that is under investigation.

Figure 3 Contour of EER results with pooled training, with various amount of data from STRONG (y-axis) and WEAK-customer(x-axis).
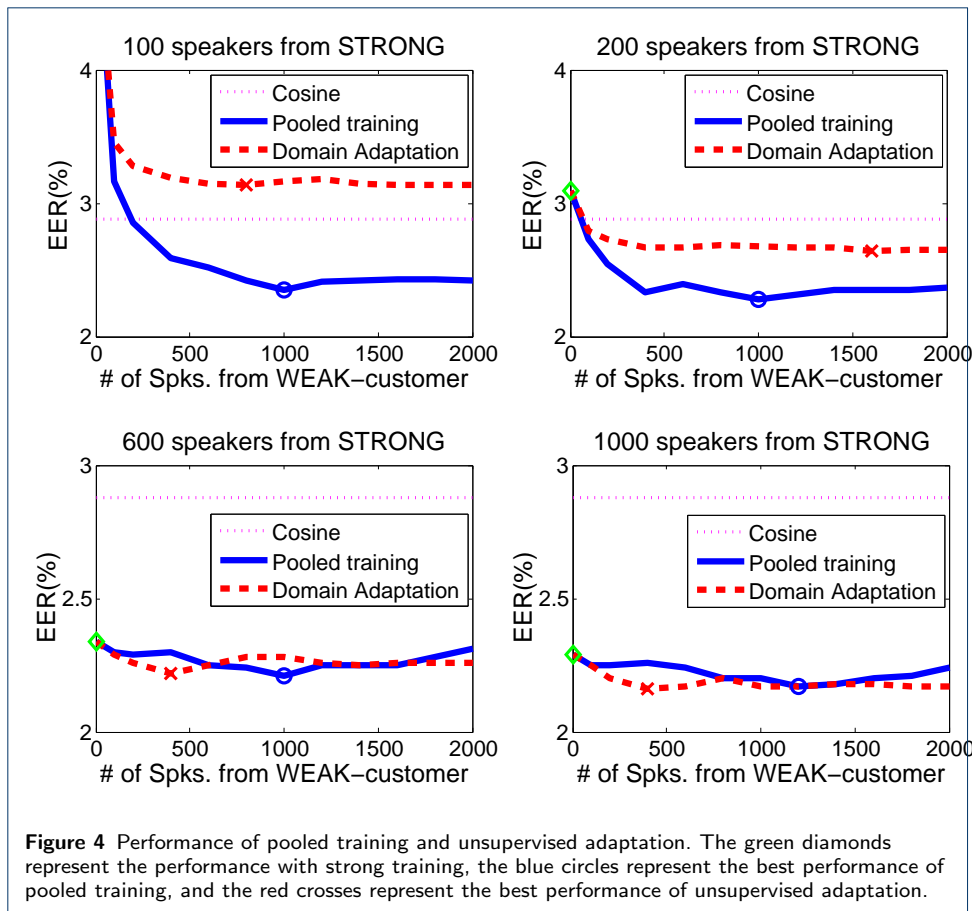
Finally, we compare the pooled training and unsupervised learning. Note that the WEAK dataset is more close to the evaluation set in the acoustic condition, so both methods play the role of model adaptation. Fig. 4 shows the results, where the four plots present configurations with different amount of human-labelled data to train the initial PLDA model. Again, only the WEAK-customer subset is used as the adaptation data.

From Fig. 4, it can be observed that if the human-labelled data are limited, both the pooled training and the unsupervised adaptation offer clear performance improvement, though the pooled training is more effective. We attribute the superiority of the pooled training to the fact that it not only adapts to the new acoustic condition, but also utilizes the speaker-related discriminant information associated with the weak labels. Since the human-labelled data are limited, the initial PLDA is not strong, and therefore the additional discriminant information is essentially valuable, leading to the clear advantage with the pooled training. If the human-labelled data are sufficient, the initial PLDA model covers most of the acoustic conditions and holds sufficient discriminative capability, diminishing the contribution of both pooled training and unsupervised adaptation.

4 Conclusion

This paper proposed a knowledge-based weak training approach for PLDA and verified its potential in speaker verification. Based on the assumption that speakers in different sessions are different, weak labels can be easily produced and used as supplemental data to train PLDA. Our experiments on a large-scale customer service archive demonstrated that the weak training approach works well when the 'different session, different speaker' assumption is held. This approach is most effective when human-labelled data are limit, even outperforming the unsupervised adaptation method. Future work will investigate the possibility to utilize both the knowledge-based weak labels and model-based weak labels, and investigate active learning to select the most valuable data for human labeling.

Figure 4 Performance of pooled training and unsupervised adaptation. The green diamonds represent the performance with strong training, the blue circles represent the best performance of pooled training, and the red crosses represent the best performance of unsupervised adaptation.

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