MULTILAYER BOOTSTRAP NETWORK FOR UNSUPERVISED SPEAKER RECOGNITION

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ABSTRACT

We apply multilayer bootstrap network (MBN), a recent proposed unsupervised learning method, to unsupervised speaker recognition. The proposed method first extracts supervectors from an unsupervised universal background model, then reduces the dimension of the high-dimensional supervectors by multilayer bootstrap network, and finally conducts unsupervised speaker recognition by clustering the low-dimensional data. The comparison results with 2 unsupervised and 1 supervised speaker recognition techniques demonstrate the effectiveness and robustness of the proposed method.

Index Terms— multilayer bootstrap network, speaker recognition, unsupervised learning.

1. INTRODUCTION

Speaker recognition aims to identify speakers from their voices. It is important in many speech systems, such as speaker diarization, language recognition, and speech recognition. Supervised methods include maximum a posteriori estimation [1, 2], linear discriminative analysis (LDA) [3, 4], support vector machines [2], deep neural networks [5, 6], etc.

Because constructing a manually-labeled corpus is laboring intensive and time-consuming, it is strongly needed to develop unsupervised speaker recognition methods. Existing methods mainly include principle component analysis (PCA), k-means clustering, Gaussian mixture model (GMM), agglomerative hierarchical clustering, and joint factor analysis. For example, Wooters and Huijbregts [7] used agglomerative clustering to merge speaker segments by Bayesian information criterion. Iso [8] used vector quantization to encode speech segments and used spectral clustering, which is a k-means clustering applied to a low-dimensional subspace of data, for speaker recognition. Nwe et al. [9] used a group of GMM clusterings to improve individual base GMM clusterings. Some methods apply clustering techniques, e.g. variational Bayesian expectation-maximization (EM) GMM [10] and spectral clustering [11], to a low-dimensional total variability subspace [4] that is learned from high-dimensional supervectors by joint factor analysis [4]. Some methods compensate the total variability space with new items, e.g. [12]. Because little prior knowledge of data is known beforehand, an unsupervised method should satisfy the following conditions: (i) no need for manually-labeled training data; (ii) no hyperparameter tuning for a satisfied performance; and (iii) robustness to different data or modeling conditions. Due to these strict requirements, unsupervised speaker recognition is a very difficult task. In this paper, we present a multilayer bootstrap network (MBN) [13] based algorithm. MBN is a recent proposed unsupervised nonlinear dimensionality reduction algorithm. Experimental results show that the proposed method satisfies these requirements.

This paper is organized as follows. In Section 2, we present the MBN-based system. In Section 3, we present the MBN algorithm and its typical hyperparameter setting. In Section 4, we present the relationship between MBN and deep learning. In Section 5, we report comparison results. In Section 6, we conclude this paper.

2. SYSTEM

Given an unlabeled speaker recognition corpus, we propose the following unsupervised algorithm:1

- The first step trains a speaker- and session-independent unsupervised universal background model (UBM) [1] from an acoustic feature, which produces a d-dimensional supervector for each utterance, denoted as \( x = [n^T, f^T]^T \) where \( n \) is the accumulation of the mixture occupation over all frames of the utterance and \( f \) is the vector form of the centered first order statistics.

- The second step reduces the dimension of \( x \) from \( d \) to \( \bar{d} \) \((\bar{d} \ll d)\) by multilayer bootstrap network (MBN) which is introduced in Section 3.

- The third step conducts \( k \)-means clustering on the low-dimensional data if the number of the underlying speakers is known, or agglomerative clustering if the number of the speakers is unknown.

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1The source code is downloadable from http://sites.google.com/site/zhangxiaolei321/speaker_recognition
3. MULTILAYER BOOTSTRAP NETWORK

The structure of MBN [13] is shown in Fig. 1. MBN is a multilayer localized PCA algorithm that gradually enlarges the area of a local region implicitly from the bottom hidden layer to the top hidden layer by high-dimensional sparse coding, and gets a low-dimensional feature explicitly by PCA at the output layer.

Each hidden layer of MBN consists of a group of mutually independent $k$-centers clusterings. Each $k$-centers clustering has $k$ output units, each of which indicates one cluster. The output units of all clusterings are concatenated as the input of their upper layer [13].

MBN is trained layer-by-layer from bottom up. For training a hidden layer given a $d$-dimensional input $\mathcal{X} = \{x_1, \ldots, x_n\}$, MBN trains each clustering independently [13]:

- **Random feature selection.** The first step randomly selects $d$ dimensions of $\mathcal{X}$ ($d \leq d$) to form a new set $\mathcal{X}' = \{x_1', \ldots, x_n'\}$. This step is controlled by a hyperparameter $a = d/d$.

- **Random sampling.** The second step randomly selects $k$ data points from $\mathcal{X}'$ as the $k$ centers of the clustering, denoted as $\{w_1, \ldots, w_k\}$. This step is controlled by a hyperparameter $k$.

- **Random reconstruction.** The third step randomly selects $d'$ dimensions of the $k$ centers ($d' \leq d'/d$) and does a one-step cyclic-shift as shown in Fig. 2. This step is controlled by a hyperparameter $r = d'/d$.

- **Sparse representation learning.** The fourth step assigns the input $\hat{x}$ to one of the $k$ clusters and outputs a $k$-dimensional indicator vector $\mathbf{h} = [h_1, \ldots, h_k]^T$. For example, if $\hat{x}$ is assigned to the second cluster, then $\mathbf{h} = [0, 1, 0, \ldots, 0]^T$. The assignment is calculated according to the similarities between $\hat{x}$ and the $k$ centers, in terms of some predefined similarity measurement at the bottom layer, such as the minimum squared loss $\arg \min_{k=1}^{k} \|w_i - x\|^2$, or in terms of $\arg \max_{k=1}^{k} w_i^T \hat{x}$ at all other hidden layers [13].

3.1 A typical hyperparameter setting

MBN has five hyperparameters $\{V, L, \{k_i\}_{i=1}^{L}, a, r\}$ where $V$ is the number of $k$-centers clusterings per layer, $L$ is the number of hidden layers, and $k_i$ is the hyperparameter $k$ at the $i$th hidden layer. As shown in [13], MBN is robust to hyperparameter selection. Here we introduce a typical setting:

- **Setting hyperparameter $k$.** (i) $k_1$ should be as large as possible, i.e. $k_1 \to n$. Suppose the largest $k$ supported by hardware is $k_{\text{max}}$, then $k_1 = \min(0.9n, k_{\text{max}})$. (ii) $k_i$ decays with a factor of, e.g. 0.5, with the increase of hidden layers. That is to say, $k_i = 0.5k_{i-1}$. (iii) $k_L$ should be larger than the number of speakers $c$. Typically, $k_L \approx 1.5c$. If $c$ is unknown, we simply set $k_L$ to a relatively large number, e.g. 30, since $c$ is unlikely larger than 30 in a practical dialog.

- **Setting hyperparameter $r$.** When a problem is small-scale, e.g. $k_1 > 0.8n$, then $r = 0.5$; otherwise, $r = 0$.

- **Setting other hyperparameters.** Hyperparameter $V$ should be at least larger than 100, typically $V = 400$. Hyperparameter $a$ is fixed to 0.5. Hyperparameter $L$ is determined by $k$.

4. RELATED WORK

The proposed method learns multilayer nonlinear transforms, which is related to deep learning (a.k.a., multilayer neural networks)—a recent advanced topic in many speech processing fields, e.g. speaker recognition [5, 6], speech recognition [14], speech separation and enhancement [15–18], speech synthesis [19], and voice activity detection [20, 21]. The aforementioned deep learning methods are all supervised ones and limited to neural networks, while the proposed method is an unsupervised one and different from neural networks.

5. EXPERIMENTS

5.1 Experimental setup

We used the training corpus of speech separation challenge (SSC) [22]. The training corpus contains 34 speakers, each
of which has 500 clean utterances. We selected the first 100 utterances (a.k.a. sessions) of each speaker for evaluation, which amounts to 3400 utterances. We set the frame length to 25 milliseconds and frame shift to 10 milliseconds, and extract a 25-dimensional MFCC feature.

For the proposed MBN-based speaker recognition, we adopted the typical parameter setting of MBN. Specifically, \( V = 400, \ a = 0.5, \ r = 0.5, \) and \( k \) were set to \( 3060-1530-765-382-191-95 \). The output of PCA was set to \{2, 3, 5, 10, 30, 50\} dimensions respectively. We assumed that the number of speakers was known, and used \( k \)-means clustering for clustering the low-dimensional data.

We compared with PCA, \( k \)-means clustering, and an LDA-based system, where the first two methods are unsupervised and the third one is supervised. For the PCA-based method, we first used the same UBM as the MBN-based method to extract high-dimensional supervectors, then reduced the dimension of the supervectors to \{2, 3, 5, 10, 30, 50\} respectively, and finally evaluated the low-dimensional output of PCA by \( k \)-means clustering. For the \( k \)-means-clustering-based method, we apply \( k \)-means clustering to the high-dimensional supervectors directly.

The LDA-based system\(^2\) uses UBM to extract a high-dimensional feature, then uses joint factor analysis to reduce the high-dimensional feature to an intermediate low-dimensional representation in an unsupervised way, and finally uses LDA, a supervised dimensionality reduction method, to reduce the intermediate representation to a low-dimensional subspace where classification is conducted by a probabilistic LDA algorithm. Since factor analysis is an unsupervised dimensionality reduction method, we set its output to \{2, 3, 5, 10, 30, 50\} dimensions respectively for comparison. We constructed a training set from the SSC corpus for this supervised method: each speaker consists of 100 training utterances, which are selected from the 400 remaining utterances of the speaker.

The performance was measured by normalized mutual information (NMI)\(^\text{[23]}\). MNI was proposed to overcome the label indexing problem between the ground-truth labels and the predicted labels. It is one of the standard evaluation metrics of unsupervised learning. The higher the NMI is, the better the performance is. We also report the classification accuracy of the LDA-based system in the Supplementary Material\(^3\) where we can see that NMI is consistent with classification accuracy.

5.2. Results

Because all comparison methods use UBM to extract speaker- and session-independent supervectors, we need to study how they behave in different UBM settings, in terms of mixture number and expectation-maximization (EM) iterations. (i)

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\(^2\)The source code is downloadable from \( \text{http://research.microsoft.com/en-us/downloads/a6262fe3-03a7-4060-a08c-0b0d037a3f5b/} \)

\(^3\)\( \text{http://sites.google.com/site/zhangxiaolei321/speaker_recognition} \)
serve that the accuracy improves gradually with the increase of the number of hidden layers.

6. CONCLUSIONS

In this paper, we have proposed a multilayer bootstrap network based unsupervised speaker recognition algorithm. The method first uses UBM to extract a high-dimensional feature from the original MFCC acoustic feature, then uses MBN to reduce the high-dimensional feature to a low-dimensional space, and finally clustering the low-dimensional data. We have compared it with the PCA-, k-means-clustering-, and LDA-based methods, where the first two methods are unsupervised and the third method is supervised. Experimental results have shown that the proposed method outperforms the unsupervised methods and approaches to the supervised method. Moreover, it is insensitive to different parameter settings of UBM and MBN, which facilitates its practical use.

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