A UNIFIED DEEP NEURAL NETWORK FOR SPEAKER AND LANGUAGE RECOGNITION

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ABSTRACT

Learned feature representations and sub-phoneme posteriors from Deep Neural Networks (DNNs) have been used separately to produce significant performance gains for speaker and language recognition tasks. In this work we show how these gains are possible using a single DNN for both speaker and language recognition. The unified DNN approach is shown to yield substantial performance improvements on the 2013 Domain Adaptation Challenge speaker recognition task (55% reduction in EER for the out-of-domain condition) and on the NIST 2011 Language Recognition Evaluation (48% reduction in EER for the 30s test condition).

Index Terms: i-vector, DNN, bottleneck features, speaker recognition, language recognition

1. INTRODUCTION

The impressive gains in performance obtained using deep neural networks (DNNs) for automatic speech recognition (ASR) [1] have motivated the application of DNNs to other speech technologies such as speaker recognition (SR) and language recognition (LR) [2, 3, 4, 5, 6, 7, 8, 9]. Two general methods of applying DNN’s to the SR and LR tasks have been shown to be effective. The first or “direct” method uses a DNN trained as a classifier for the intended recognition task. In the direct method the DNN is trained to discriminate between speakers for SR [5] or languages for LR [4]. The second or “indirect” method uses a DNN trained for a different purpose to extract data that is then used to train a secondary classifier for the intended recognition task. Applications of the indirect method have used a DNN trained for ASR to extract frame-level features [2, 3, 10], accumulate a multinomial vector [7] or accumulate multi-modal statistics [6, 8] that were then used to train an i-vector system [11, 12].

The unified DNN approach described in this work uses two of the indirect methods described above. The first indirect method (“bottleneck”) uses frame-level features extracted from a DNN with a special bottleneck layer [13] and the second indirect method (“DNN-posterior”) uses posteriors extracted from a DNN to accumulate multi-modal statistics [6]. The features and the statistics from both indirect methods are then used to train four different i-vector systems: one for each task (SR and LR) and each method (bottleneck and DNN-posterior). A key point in the unified approach is that a single DNN is used for all four of these i-vector systems. Additionally, we will examine the feasibility of using a single i-vector extractor for both SR and LR.

2. I-VECTOR CLASSIFIER FOR SR AND LR

Over the past 5 years, state-of-the-art SR and LR performance has been achieved using i-vector based systems [11]. In addition to using an i-vector classifier as a baseline approach for our experiments, we will also show how phonetic-knowledge rich DNN feature representations and posteriors can be incorporated into the i-vector classifier framework providing significant performance improvements. In this section we provide a high-level description of the i-vector approach (for a detailed description see, for example, [11, 14]).

In Figure 1 we show a simplified block diagram of i-vector extraction and scoring. An audio segment is first processed to find the locations of speech in the audio (speech activity detection) and to extract acoustic features that convey speaker/language information. Typically 20 dimensional mel-frequency cepstral coefficients (MFCC) and derivatives are used for SR and 56 dimensional static cepstra plus shifted-delta cepstra (SDC) are used for LR analyzed at 100 feature vectors/second. Using a Universal Background Model (UBM), essentially a speaker/language-independent Gaussian mixture model (GMM), the per-mixture posterior probability (“GMM-posterior”) is computed and used, along with the feature vectors in the segment, to accumulate zeroth, first, and second order sufficient statistics (SS). These SSs are then transformed into a low dimensional i-vector representation (typically 400-600 dimensions) using a total variability matrix, T. The i-vector is whitened by subtracting a global mean, m, scaled by the inverse square root of a global covariance matrix, W, and then normalized to unit length [14]. Finally, a score between a model and test i-vector is computed. The simplest scoring function is the cosine dis-
tance between the i-vector representing a speaker/language model (average of i-vectors from the speaker’s/language’s training segments) and the i-vector representing the test segment. The current state-of-the-art scoring function, called Probabilistic Linear Discriminant Analysis (PLDA) [14], requires a within-class matrix $\Sigma_{wc}$, characterizing how i-vectors from a single speaker/language vary, and an across class matrix $\Sigma_{ac}$, characterizing how i-vectors between different speakers/languages vary.

Collectively, the UBM, $T$, $W$, $m$, $\Sigma_{wc}$, and $\Sigma_{ac}$ are known as the system’s hyper-parameters and must be estimated before a system can enroll and/or score any data. The UBM, $T$, $W$, and $m$ represent general feature distributions and total variance of statistics and i-vectors, so unlabeled data from the desired audio domain (i.e., telephone, microphone, etc.) can be used to estimate them. The $\Sigma_{wc}$ and $\Sigma_{ac}$ matrices, however, each require a large collection of labeled data for training. For SR, $\Sigma_{wc}$ and $\Sigma_{ac}$ typically require thousands of speakers each of whom contributes tens of samples to the data set. For LR, the enrollment samples from each desired language, which typically hundreds of samples from many different speakers, can be used to estimate $\Sigma_{wc}$ and $\Sigma_{ac}$.

By far the most computationally expensive part of an i-vector system is extracting the i-vectors themselves. An efficient approach for performing both SR and LR on the same data is to use the same i-vectors. This may be possible if both systems use the same feature extraction, UBM, and T matrices. There may be some tradeoff in performance however since the UBM, T matrix, and signal processing will not be specialized for SR or LR.

3. DEEP NEURAL NETWORK CLASSIFIER FOR SPEECH APPLICATIONS

3.1. DNN architecture

A DNN, like a multi-layer perceptron (MLP), consists of an input layer, several hidden layers and an output layer. Each layer has a fixed number of nodes and each sequential pair of layers are fully connected with a weight matrix. The activations of nodes on a given layer are computed by transforming the output of the previous layer with the weight matrix: $a^{(i)} = W^{(i)}x^{(i-1)}$. The output of a given layer is then computed by applying an “activation function” $x^{(i)} = h^{(i)}(a^{(i)})$ (see Figure 2). Commonly used activation function include the sigmoid, the hyperbolic tangent, rectified linear units and even a simple linear transformation. Note that if all the activation functions in the network are linear then the stacked matrices reduce to a single matrix multiply.

The type of activation function used for the output layer depends on what the DNN is used for. If the DNN is trained as a regression the output activation function is linear and the objective function is the mean squared error between the output and some target data. If the DNN is trained as a classifier then the output activation function is the soft-max and the objective function is the cross entropy between the output and the true class labels. For a classifier, each output node of the DNN classifier correspond to a class and the output is an estimate of the posterior probability of the class given the input data.

3.2. DNN Training for ASR

DNN classifiers can be used as acoustic models in ASR systems to compute the posterior probability of a sub-phonetic unit (a “senone”) given an acoustic observation. Observations, or feature vectors, are extracted from speech data at a fixed sample rate using a spectral technique such as filterbank analysis, MFCC, or perceptual linear prediction (PLP) coefficients. Decoding is performed using a hidden Markov model (HMM) and the DNN to find the most likely sequence of senones given the feature vectors (this requires using Bayes’ rule to convert the DNN posteriors to likelihoods). Training the DNN requires a significant amount of manually transcribed speech data [1]. The senones labels are derived from the transcriptions using a phonetic dictionary and a state-of-the-art GMM/HMM ASR system. Generally speaking, a refined set of phonotactic units aligned using a high performing ASR system is required to train a high performing DNN system [1].

DNN training is essentially the same as traditional MLP training. The most common approach uses stochastic gradient descent (SGD) with a mini-batch for updating the DNN parameters throughout a training pass or “epoch”. The backpropagation algorithm is used to estimate the gradient of the DNN parameters for each mini-batch. Initializing the DNN is critical, but it has been shown that a random initialization is
adequate for speech applications where there is a substantial amount of data [13]. A held out validation data set is used to estimate the error rate after each training epoch. The SGD algorithm uses a heuristic learning rate parameter that is adjusted in accordance with a scheduling algorithm which monitors the validation error rate at each epoch. Training ceases when the error rate can no longer be reduced.

In the past, training neural networks with more than 2 hidden layers proved to be problematic. Recent advances in fast and affordable computing hardware, optimization software and initialization techniques have made it possible to train much deeper networks. A typical DNN for ASR will have 5 or more hidden layers each with the same number of nodes - typically between 500 and 3,000 [1]. The number of output senones varies from a few hundred to tens of thousands [15].

### 3.3. DNN bottleneck features

A DNN can also be used as a means of extracting features for use by a secondary classifier - including another DNN [16]. This is accomplished by sampling the activation of one of the DNN’s hidden layers and using this as a feature vector. For some classifiers the dimensionality of the hidden layer is too high and some sort of feature reduction is necessary like LDA or PCA. In [13], a dimension reducing linear transformation is optimized as part of the DNN training by using a special bottleneck hidden layer that has fewer nodes (see Figure 2). The bottleneck layer uses a linear activation so that it behaves very much like a LDA or PCA transformation on the activation of the previous layer. The bottleneck DNN used in this work is the same system described in [13]. In theory any layer can be used as a bottleneck layer, but in our work we have chosen to use the second to last layer with the hope that the output posterior prediction will not be too adversely affected by the loss of information at the bottleneck.

### 3.4. DNN stats extraction for an i-vector system

A typical i-vector system uses zeroth, first and second order statistics generated using a GMM. Statistics are accumulated by first estimating the posterior of each GMM component density for a frame (the “occupancy”) and using these posteriors as weights for accumulating the statistics for each component of the mixture distribution. The zeroth order statistics are the total occupancies for an utterance across all GMM components and the first order statistics are the weighted sum of the means per a component. The i-vector is then computed using a dimension reducing transformation that is non-linear with respect to the zeroth order statistics.

An alternate approach to extracting statistics has been proposed in [6]. Statistics are accumulated in the same way as for the GMM but class posteriors from the DNN are used in place of GMM component posteriors. Once the statistics have been accumulated, the i-vector extraction is performed in the same way as it is from the GMM based statistics. This approach has been shown to give significant gains for both SR and LR [6,7,17].

### 4. EXPERIMENT SETUP

#### 4.1. Corpora

Three different corpora are used in our experiments. The DNN itself is trained using a 100 hours subset of Switchboard 1 [18]. The 100 hour Switchboard subset is defined in the example system distributed with Kaldi [19]. The SR systems were trained and evaluated using the 2013 Domain Adaptation Challenge (DAC13) data [20]. The LR systems were evaluated on the NIST 2011 Language Recognition Evaluation (LRE11) data [21]. Details on the LR training and development data can be found in [22].

#### 4.2. System configuration

##### 4.2.1. Commonalities

All systems use the same speech activity segmentation generated using a GMM based speech activity detector (GMM SAD). The i-vector system uses MAP and PPCA to estimate the T matrix. Scoring is performed using PLDA [14]. With the exception of the input features or multi-modal statistics, the i-vector systems are identical and use a 2048 component GMM UBM and a 600 dimensional i-vector subspace. All LR systems use the discriminative backend described in [22].

##### 4.2.2. Baseline systems

The front-end feature extraction for the baseline SR system uses 7 static cepstra appended with 49 SDC. Unlike the front-end described in [22], vocal track length normalization (VTLN) and feature domain nuisance attribute projection (NAP) are not used. The front-end for the baseline SR system uses 20 MFCCs including C0 and their first derivatives for a total of 40 features.

#### 4.2.3. DNN system

The DNN was trained using 4,199 state cluster (“senone”) target labels generated using the Kaldi Switchboard 1 “tri4a” example system [19]. The DNN front-end uses 13 Gaussianized PLP coefficients and their first and second order derivatives (39 features) stacked over a 21 frame window (10 frames to either side of the center frame) for a total of 819 input features. The GMM SAD segmentation is applied to the stacked features.

The DNN has 7 hidden layers of 1024 nodes each with the exception of the 6th bottleneck layer which has 64 nodes. All hidden layers use a sigmoid activation function with the exception of 6th layer which is linear[13]. The DNN training is preformed on an nVidia Tesla K40 GPU using custom software developed at MIT/CSAIL.
## 5. EXPERIMENT RESULTS

### 5.1. Speaker recognition experiments

Two sets of experiments were run on the DAC13 corpora: “in-domain” and “out-of-domain”. For both sets of experiments, the UBM and T hyper-parameters are trained on Switchboard (SWB) data. The other hyper-parameters (the W, m, \( \Sigma \), and \( \Sigma_{ac} \)) are trained on 2004-2008 speaker recognition evaluation (SRE) data for the in-domain experiments and SWB data for the out-of-domain experiments (see [22] for more details). Tables 1 and 2 summarize the results for the in-domain and out-of-domain experiments with the first row of each table corresponding to the baseline system. While the DNN-posterior technique with MFCCs gives a significant gain over the baseline system for both sets of experiments, as also reported in [6] and [17], an even greater gain is realized using bottleneck features with a GMM. Unfortunately, using both bottleneck features and DNN-posteriors degrades performance.

### 5.2. Language recognition experiments

The experiments run on the LRE11 task are summarized in Table 3 with the first row corresponding to the baseline system and the last row corresponding to a fusion of 5 “post-evaluation” systems (see [22] for details). Bottleneck features with GMM posteriors outperforms the other systems configurations including the 5 system fusion. Interestingly, bottleneck features with DNN-posteriors show more of an improvement over the baseline system than in the speaker recognition experiments.

## 5.3. Cross-task i-vector Extraction

Table 4 shows the performance on the DAC13 and LRE11 tasks when extracting i-vectors using parameters from one of the two systems. As expected, there is a degradation in performance for the mis-matched task, but the degradation is less on the DAC13 SR task using the LRE11 LR hyper-parameters. These result motivate further research in developing a unified i-vector extraction system for both SR and LR by careful UBM/T training data selection.

## 6. CONCLUSIONS

This paper has presented a DNN bottleneck feature extractor that is effective for both speaker and language recognition and produces significant performance gains over state-of-the-art MFCC/SDC i-vector approaches as well as more recent DNN-posterior approaches. For the speaker recognition DAC13 task, the new DNN bottleneck features decreased in-domain EER by 26% and DCF by 33% and out-of-domain EER by 55% and DCF by 47%. The out-of-domain results are particularly interesting since no in-domain data was used for DNN training or hyper-parameter adaptation. On LRE11, the same bottleneck features decreased EERs at 30s, 10s, and 3s test durations by 48%, 39%, and 24%, respectively, and even out performed a 5 system fusion of acoustic and phonetic based recognizers. A final set of experiments demonstrated that it may be possible to use a common i-vector extractor for a unified speaker and language recognition system. Although not presented here, it was also observed that recognizers using the new DNN bottleneck features produced much better calibrated scores as measured by CLLR metrics.

The DNN bottleneck features, in essence, are the learned feature representation from which the DNN posteriors are derived. Experimentally, it appears that using the learned feature representation is better than using just the output posteriors with SR or LR features, but combining the DNN bottleneck features and DNN posteriors degrades performance. This may be because we are able to train a better suited posterior estimator (UBM) with data more matched to the task data. Since we are working with new features, future research will examine whether there are more effective classifiers to apply than i-vectors. Other future research will explore the sensitivity of the bottleneck features to the DNN’s configuration, and training data quality and quantity.

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