A Multi-layered Acoustic Tokenizing Deep Neural Network (MAT-DNN) for Unsupervised Discovery of Linguistic Units and Generation of High Quality Features

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Abstract

This paper summarizes the work done by the authors for the Zero Resource Speech Challenge organized in the technical program of Interspeech 2015. The goal of the challenge is to discover linguistic units directly from unlabeled speech data. The Multi-layered Acoustic Tokenizer (MAT) proposed in this work automatically discovers multiple sets of acoustic tokens from the given corpus. Each acoustic token set is specified by a set of hyperparameters that describe the model configuration. These sets of acoustic tokens carry different characteristics of the given corpus and the language behind them as a result of mutual reinforcement. The multiple sets of token labels are then used as the targets of a Multi-target DNN trained on low-level acoustic features. Bottleneck features extracted from the MDNN are used as feedback for the MAT and the MDNN itself. We call this iterative system the Multi-layered Acoustic Tokenizing Deep Neural Network (MAT-DNN) which generates high quality features for track 1 of the challenge and acoustic tokens for track 2 of the challenge.

Index Terms: zero resource, unsupervised learning, dnn, hmm

1. Introduction

Human infants acquire knowledge of a language by mere immersion in a language speaking community. The process is not yet completely understood, and is difficult to be reproduced by current automatic speech recognition (ASR) technologies where the dominant paradigm is supervised learning with large human-annotated data sets\cite{1}. The idea behind the Zero Resource Speech Challenge is to inspire the development of speech recognition under the extremes situation where a whole language has to be learned from scratch\cite{1}. The goal of this challenge is to find linguistic units directly from raw audio with no knowledge of the language, the speaker, or any other supplementary information. This challenge includes two tracks which focuses on subword units and word units respectively. In the first track of unsupervised subword modeling, the aim is to construct a framework that can be trained with the label set \( \omega \). The second track focuses on discovery of word units and the aim is to extract timing information of word units in the hypothesized vocabularies derived from the speech corpus. The intervals in which each word unit appears in the corpus is then evaluated on parsing, clustering and matching quality\cite{6}. This paper serves as the documentation for the work by a team organized in the technical program of Interspeech 2015. The goal in this step is to obtain multiple sets of acoustic tokens, each defined by some hyperparameters, which capture complementary aspects of the corpus. There is no knowledge regarding the corpus at all, so the process here is completely unsupervised.

2. Proposed Approach

2.1. Overview of the proposed framework

The framework of the approach is shown in Fig 1. In the left part, the Multi-layered Acoustic Tokenizer (MAT) produces many sets of acoustic tokens using unsupervised HMMs, each describing different aspects of the given corpus. These tokens are specified by two hyperparameters describing HMM configurations. A set of acoustic tokens is obtained for each configuration by iteratively optimizing the token models and the token labels on the given acoustic corpus. Multiple pairs of hyperparameters were selected producing multi-layered token labels for the given corpus to be used as the training targets of the Multi-target Deep Neural Network (MDNN) on the right part of Fig 1. The MDNN on the right learns its parameters based on the multi-layered token labels for the given corpus as its targets from the MAT on the left, so the knowledge carried by different token sets on different layers are fused. Bottleneck features are then extracted from this MDNN. In the first iteration, some initial acoustic features are used for both the MAT and the MDNN. This gives the first set of bottleneck features. These bottleneck features are then used as feedback to both the MAT (to replace the initial acoustic features) and the MDNN (to be concatenated with the initial acoustic features to produce tandem features) in the second iteration. Such feedback can be continued iteratively. The complete framework is referred to as Multi-layered Acoustic Tokenizing Deep Neural Network (MAT-DNN) in this paper. The output of the MDNN (bottleneck features) is evaluated in Track 1 of the Challenge. The time intervals for the acoustic token labels at the output of the MAT are evaluated in Track 2 of the Challenge.

2.2. Multi-layered Acoustic Tokenizer

The goal in this step is to obtain multiple sets of acoustic tokens, each defined by some hyperparameters, which capture complementary aspects of the corpus. There is no knowledge regarding the corpus at all, so the process here is completely unsupervised.

2.2.1. Unsupervised Token Discovery for Each layer of MAT

Using unsupervised HMMs, it is straightforward to discover acoustic tokens from the corpus for a chosen hyperparameter pair \((\theta, \omega)\) which determines the HMM configuration (number of states per model and number of distinct models)\cite{1,2,12,13,14}. This can be achieved by first finding an initial label set \(\omega_0\) based on the assumption that all features in the corpus \(X\) as in eq \(1\). Then in each iteration \(t\) the HMM parameters \(\theta_t\) can be trained with the label set \(\omega_{t-1}\) obtained in the previous iteration as in \(2\), and the new label set \(\omega_t\) can be obtained by token decoding with the obtained parameters \(\theta_t\) as in \(3\).

\[
\omega_0 = \text{initialization}(X),
\]

\[
\theta_0^{\psi} = \arg \max P(X|\theta_0^{\psi}, \omega_{t-1}),
\]

\[
\omega_t = \arg \max P(X|\theta_t^{\psi}, \omega).
\]
The training process can be repeated with enough number of iterations until a converged set of token HMMs is obtained. The processes (2), (3) are referred to as token model optimization and token label optimization in the left part of Fig.1.

2.2.2. Granularity Space of Multi-layered Acoustic Token Sets

The process explained above can be performed with different HMM configurations, each characterized by two hyperparameters: the number of states \( m \) in each acoustic token HMM, and the total number of distinct acoustic tokens \( n \) during initialization, \( \psi = (m, n) \). The transcription of a signal decoded with these tokens can be considered as a temporal segmentation of the signal, so the HMM length (or number of states in each HMM) \( m \) represents the temporal granularity. The set of all distinct acoustic tokens can be considered as a segmentation of the phonetic space, so the total number \( n \) of distinct acoustic tokens represents the phonetic granularity. This gives a two-dimensional representation of the acoustic token configurations in terms of temporal and phonetic granularities as in Fig.2. Any point in this two-dimensional space in Fig.2 corresponds to all acoustic token configurations. Acoustic tokens in different layers have different model granularities that extract complementary characteristics of the corpus and the language behind, so they jointly capture knowledge about the corpus. Although the selection of the hyperparameters can be arbitrary in the above two-dimensional space, here we can select \( M \) temporal granularities \((n=m_1, m_2, ..., m_M)\) and \( N \) phonetic granularities \((n=n_1, n_2, ..., n_N)\), forming a two-dimensional array of \( M \times N \) hyperparameter pairs in the granularity space.

2.3. Mutual Reinforcement of Multi-layered Tokens

Because all the layers obtained in the MAT above are learned in an unsupervised fashion, they are not precise. But we have many layers, each corresponding to a different pair of hyperparameters \( \psi = (m, n) \), so they can be mutually reinforced. This is explained here and shown in Fig.3 including token boundary fusion and LDA-based token label re-initialization as in Fig.3(b).

2.3.1. Token Boundary Fusion

Fig.3(c) shows the token boundary when a part of an utterance is segmented into acoustic tokens on different layers with different hyperparameter pairs \( \psi = (m, n) \). We define a boundary function \( b_{m,n}(j) \) on each layer with \( \psi = (m, n) \) for the possible boundary between every pair of two adjacent frames within the utterance, where \( j \) is the time index of such possible boundaries. On each layer \( b_{m,n}(j) = 1 \) if \( \text{boundary } j \) is a token boundary and 0 otherwise. All these boundary functions \( b_{m,n}(j) \) for all different layers are then weighted and averaged to give a joint boundary function \( B(j) \). The weights consider the fact that smaller \( m \) or shorter HMMs generate more boundaries. The peaks of \( B(j) \) are then selected based on the second derivatives and some filtering and thresholding process. This gives the new segmentation of the utterance as shown at the bottom of Fig.3(c).

2.3.2. LDA-based Token Label Re-initialization

As shown in Fig.3(e), each new segment obtained above usually consists of a sequence of acoustic tokens on each layer based on the tokens defined on that layer. We now consider all the tokens on all the different layers as different words, so we have a vocabulary of \( \sum_{i=1}^{MN} n_i \) words, i.e., there are \( n_i \) words on the \( i \)-th layer and there are a total of \( MN \) layers. A new segment here is thus considered as a document (bag-of-words) composed of words (tokens) collected from all different layers. Latent Dirichlet Allocation (LDA) is performed for topic modeling, and then each document (new segment) is labeled with the most probable topic. Because in LDA a topic is characterized by a word distribution, here a token distribution across different layers may also represent a certain acoustic characteristics or a certain acoustic token. By setting the number of topics in LDA as the number of distinct tokens \( n = n_1, n_2, ..., n_N \) as in subsection 2.2.2) we have a new initial label set \( \omega_0 \) as in (1) of subsection 2.2.1) in which each new segment obtained here is a new acoustic token whose ID is the topic ID obtained by LDA. This new initial label set \( \omega_0 \) is then used to re-train all the acoustic tokens on all layers of MAT as in (1).
2.4. The Multi-target DNN (MDNN)

As shown in the right part of Fig.1 token label sequence from a layer (with a pair of hyperparameters \(\psi = (m, n)\)) is a valid target for supervised framewise training, although obtained in an unsupervised way. In the initial work here, we do not use the HMM states as the target, but simply take the token label as the training target. As shown in Fig.2 there are multi-layered token labels with different hyperparameter pair \(\psi = (m, n)\) for each utterance, so we jointly consider all the multi-layered token labels by learning the parameters for a single DNN with a uniformly weighted cross-entropy objective at the output layer. As a result, the bottleneck feature (BNF) extracted from this DNN automatically fuse all knowledge about the corpus and the language behind learned from the different sets of acoustic tokens.

2.5. The Iterative Learning Framework for MAT-DNN

Once the BNFs are extracted from the MDNN in iteration 1, they can be taken as the input of the MAT on the left of Fig.1(c) replacing the initial acoustic features. The MAT then generates updated multi-layered token labels and these updated sets of multi-layered token labels can be used as the updated training objective of the MDNN. The input features of the MDNN can also be updated by concatenating the initial acoustic features with the newly extracted BNFs as the tandem features. This process can be repeated for several iterations until satisfactory results are obtained.

The tandem feature used as the input of the MDNN can be further augmented by concatenating unsupervised features obtained in other systems such as Deep Boltzmann Machine\[17\] (DBM) posteriorgrams, Long-Short Term Memory Recurrent Neural Network\[18\] (LSTM-RNN) autoencoder bottleneck features, and i-vectors\[19\] trained on MFCC. Although extracted from the conventional token labeling (RNN) in which the recurrent structure is included in back propagation training, the concatenation of the bottleneck features with other features in the next iteration in MDNN is a kind of recurrent structure.

3. Experimental Setup

The general framework of the MAT-DNN presented above allows several flexible configurations. However, in this work, we train the MAT-DNN in the following manner. We set \(n=3, 5, 7, 9\) states per token HMM and \(n=50, 100, 300, 500\) distinct tokens in the MAT, which gives a total of 16 layers.

In the first iteration, we use the 39 dimension Mel-frequency Cepstral Coefficients (MFCC) with energy, delta and double delta as the initial acoustic features for the input to both the MAT and the MDNN. We tandem the MFCC with a window of 4 frames before and after the input tokens, and an i-vector (400 dimensions) trained on the BNF of each evaluation interval for the input of the MDNN. The topology of the MDNN is set to be \(751(\text{input})\)\(\rightarrow\)256(hidden)\(\rightarrow\)256(hidden)\(\rightarrow\)39(bottleneck)\(\rightarrow\)target.

Although extracted from the conventional recurrent neural network (RNN) in which the recurrent structure is included in back propagation training, the concatenation of the bottleneck features with other features in the next iteration in MDNN is a kind of recurrent structure.

3.1. Track 1

The two official corpora are the Buckeye corpus\[27\] and NCHLT Xitsonga Speech corpus\[28\] in English and Tsonga respectively. They are used in the evaluation based on the ABX discriminability test\[4\] including across and within speaker tests. The final results is in error percentage, which means the lower the better. Our results of track 1 is presented in Table I.

Rows (1) and (11) are the official baseline MFCC features and official topline supervised phone posteriorgrams provided by the challenge organizers respectively. Row (2) is our baseline of the MFCC features, the initial acoustic features used to train all systems in this work. Row (3) is for the DBM posteriorgrams extracted from the MFCC of row (2), serving as a strong unsupervised baseline. The results in rows (4), (5) and (6) are the performance of the bottleneck features extracted in the first iteration of the MAT-DNN without applying mutual reinforcement (MR) (4), applying MR once (5), and twice (6) respectively. Row (7) is similar to row (5), except we use a wider bottleneck layer with 256 dimensions instead of 39. Rows (7) and (8) are the performance of the bottleneck features extracted in the second iteration of the MAT-DNN without applying MR once (8), The MAT of the MAT-DNN in (7) and (8) is trained using the BNF of row(5). Row (10) is similar to row (8), except only the MFCC and i-vectors are tandem as input without other features.

All the features from row (2) to (10) except for (9) are confined to 39 phonemes in the language. Also, a general trend is that larger values of \(m\) and \(n\) seem better, probably because \(n=50\) is close to the total number of phonemes in the language. Also, a general trend is that larger values...
Table 2: Comparison of three typical example token sets selected out of all shown in Fig. 4 with the JHU baseline. Those better than JHU baseline are in bold.

|      | NED Cov. | Matching | Grouping | Type | Token | Boundary |
|------|----------|----------|----------|------|-------|----------|
|      | (%)      |          |          |      |       |          |
| Eng. |          |          |          |      |       |          |
| JHU  | 21.9     | 16.3     | 39.4     | 1.6  | 3.1   | 21.4     | 84.6     | 33.3     | 6.2  | 1.9  | 2.9   | 5.5  | 0.4  | 0.8   | 44.1 | 4.7  | 8.6   |
| (A)  | 87.5     | 100      | 1.4      | 0.5  | 0.8   | 3.6      | 18.7     | 6       | 4.2  | 11.9 | 6.2   | 8.3  | 15.7 | 10.9  | 35.2 | 84.6 | 49.8  |
| JHU  | 12       | 16.2     | 69.1     | 0.3  | 0.5   | 52.1     | 77.4     | 62.2    | 3.2  | 1.4  | 2.6   | 0.5  | 0.8   | 22.3  | 5.6  | 8.9   |
| Tso. |          |          |          |      |       |          |
| JHU  | 69.1     | 95       | 5.9      | 0.5  | 0.9   | 10.7     | 26.8     | 15.3    | 1.5  | 3.9  | 2.3   | 6.6  | 3.4   | 17.1  | 59.1 | 26.6  |
| (B)  | 56.2     | 96.1     | 9.7      | 0.4  | 0.8   | 13.5     | 12.7     | 13.1    | 1.8  | 4.7  | 2.5   | 3.9  | 9.1   | 5.4   | 21.2 | 62.1 | 31.6  |

Figure 4: Results for Track 2 for (a) English and (b) Tsonga. Each subgraph is an evaluation measure for four cases of token sets used to train the bottleneck features listed in four rows of Table 1 as shown at the bottom. The four bars in each group for a value of $m$ are for $n=50$, 100, 300, 500 from left to right (not shown in the figure) and $\psi = (m, n)$ are parameters for the token sets. Blue, yellow and white bars correspond to better, equal to or worse as compared to the JHU baseline at the upper left corner of each subgraph. The coverage is not shown because it is almost 100% in all cases.

We selected three typical example token sets (A)(B)(C) out of the many proposed here and shown in Fig. 4 and compared them with the JHU baseline in Table 2 including Precision (P), Recall (R) and F-scores (F). These three example sets are also marked in Fig. 4. In Table 2 those better than JHU baseline are in bold. The much higher NED and coverage scores suggest that the proposed approach is a highly permissive matching algorithm. The much higher parsing scores (type, token and boundary scores), especially the Recall and F-scores, imply the proposed approach is more successful in discovering word-like units. However, the matching and grouping scores are much worse probably because the discovered tokens cover almost the whole corpus, including short pauses or silence, and therefore many tokens are actually noises. Another possible reason might be that the values of $n$ used are much smaller than the size of the real word vocabulary, making the same token label used for signal segments of varying characteristics and this degenerated the grouping qualities.

4. Conclusion
This paper summarizes the preliminary work done for the Zero Resource Speech Challenge in Interspeech 2015. We propose a MAT-DNN to generate multi-layer token sets and fuse the various knowledge in different token sets in the bottleneck features. We present the complete results on all evaluations we tested up to the submission deadline, with a hope that these results serve as good references for future investigations.
5. References

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