Unsupervised Domain Adaptation by Adversarial Learning for Robust Speech Recognition

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Abstract

In this paper, we investigate the use of adversarial learning for unsupervised adaptation to unseen recording conditions, more specifically, single microphone far-field speech. We adapt neural networks based acoustic models trained with close-talk clean speech to the new recording conditions using untranscribed adaptation data. Our experimental results on Italian SPEECON data set show that our proposed method achieves 19.8% relative word error rate (WER) reduction compared to the unadapted models. Furthermore, this adaptation method is beneficial even when performed on data from another language (i.e. French) giving 12.6% relative WER reduction.

1 Introduction

Recently with the success of deep learning methods, automatic speech recognition (ASR) has achieved human performance in conversational speech recognition [1,2]. However, far-field speech, especially when recorded with a single microphone, remains one of the major obstacles to achieving complete human parity, mainly because of challenging environments with a lot of noises and reverberations [3–7]. Also, far-field speech, especially when recorded with a single microphone and in a far-field scenario. We explore both cases, within the language (Italian) and language mismatch (Italian as target language and adaptation data is French) and compare its efficiency with other supervised training methods. To the best of our knowledge, this study is the first evaluation of unsupervised domain adaptation for ASR in a crosslingual setup.

2 Method

Inspired by [27], we first perform regular training of DNN acoustic model on labeled source domain data (clean speech) and then adapt learned weights using mixture of same labeled source domain data and unlabeled target domain data (noisy reverberated speech). An overview of the method is shown in Fig. 1. At the training stage, we only use data samples from the source domain \( X_s = \{x_1^s, ..., x_N^s\} \) and corresponding senone labels \( Y^s = \{y_1^s, ..., y_N^s\} \). Based on DNN parameters \( \theta \), we calculate predicted senone labels \( \hat{Y}^s = \{\hat{y}_1^s, ..., \hat{y}_N^s\} \) and the value of cross-entropy loss function

\[
L_y(\theta) = -\frac{1}{N^s} \sum_{i=1}^{N^s} \log P(\hat{y}_i^s | x_i^s; \theta),
\]

The parameters are then updated via back-propagation for minimization of the loss function:

\[
\theta \leftarrow \theta - \epsilon \frac{\partial L_y}{\partial \theta},
\]
where $\epsilon$ is the learning rate.

At the adaptation stage, we use the same data samples from the source domain $X^s = \{x^s_1,\ldots,x^s_N\}$ and corresponding senone labels $Y^s = \{y^s_1,\ldots,y^s_N\}$. We also add data samples from the target domain $X^t = \{x^t_1,\ldots,x^t_M\}$, for which we do not have senone labels. In addition to that, we introduce secondary task of domain classification.

The set of parameters $\theta$, which were learned at the training stage, is decomposed into two sets: the parameters of the first $f$ hidden layers $\theta_f$, which are shared between the senone and domain classification tasks and act as a feature extractor, and the rest of the parameters $\theta_d$, which are used by senone classification part of DNN. New set of parameters $\theta_d$ is added for the domain classification task. Loss functions for the senone and domain classification tasks are defined as follows:

$$L_y(\theta_f, \theta_y) = -\frac{1}{N^s} \sum_{i=1}^{N^s} \log P(\hat{y}^s_i = y^s_i|x^s_i; \theta_f, \theta_y)$$

(3)

$$L_d(\theta_f, \theta_d) = -\frac{1}{N^s} \sum_{i=1}^{N^s} \log P(\hat{d}^s_i = 1|x^s_i; \theta_f, \theta_d)$$

(4)

Note that we do not take into account senone label predictions for the target domain data samples $X^t$, because we do not know true senone labels for them. Task specific parameters are updated to minimize corresponding loss functions:

$$\theta_y \leftarrow \theta_y - \epsilon \frac{\partial L_y}{\partial \theta_y}$$

(5)

$$\theta_d \leftarrow \theta_d - \epsilon \frac{\partial L_d}{\partial \theta_d}$$

(6)

The update of shared parameters is performed so that it minimizes the senone classification loss function and maximizes the domain classification loss function:

$$\theta_f \leftarrow \theta_f - \epsilon \left( \frac{\partial L_y}{\partial \theta_f} - \lambda \frac{\partial L_d}{\partial \theta_f} \right)$$

(7)

Maximization of the domain classification loss function aims making the output of the last shared hidden layer as less informative for the domain classifier as possible, and thus similar for data samples from different domains. The negative coefficient $-\lambda$ is responsible for that and for the balance between the importance of this task and the primary task of senone classification. $\lambda$ is initially set to 0 and is increased gradually in the training process according to the following function:

$$\lambda_c = \min\left(\epsilon \frac{c}{10}, 1\right)\lambda$$

(8)

where $\lambda_c$ is the value of gradient reversal coefficient used during epoch $c$. That is done in order to allow the senone classification part of DNN to adjust its parameters to the output of the feature layer, which would be changed too fast by the domain classification part of DNN otherwise.

### 3 Experimental Setup

#### 3.1 Datasets

SPEECON is a family of speech corpora purpose for the development of speech recognition in consumer devices. The corpora were recorded for many languages according to the common specifications what allows us to evaluate the propose method in case of language mismatch while other conditions are not altered in a significant way. We use Italian data set for all the experiments and French as adaptation data in the cross-lingual experiment. Each corpus contains recordings of read and spontaneous speech by 550 adult speakers. The recordings are made in four acoustic environments: office, entertainment, public place and car. Each recording is made with 4 microphones located on different distances from the speaker that are represented by 4 channels in SPEECON corpora:

- Channel 1 corresponds to a close distance headset microphone placed right in front of the speaker’s mouth;
- Channel 2 corresponds to a lavalier microphone placed below the chin of the speaker;
- Channel 3 corresponds to a middle distance microphone placed in 0.5–1.0 meters from the speaker;
- Channel 4 corresponds to a far distance omni-directional microphone in office and entertainment environments or middle distance otherwise.

Transcriptions are converted to lower case and cleaned up from punctuation marks. Summary of the used corpora is given in Tab. 1.

In addition to that, 197 millions words of Italian Deduplicated CommonCrawl Text are used to build Italian language model. Italian dictionary ILE with pronunciations for 588k words is used as a lexicon.

#### 3.2 Baseline

Our DNN-Hidden Markov Model (HMM) acoustic model is a multilayer perceptron consisting of 8 hidden fully connected layers with 1024 units each and output layer with
9315 units corresponding to senones (HMM states). Sigmoid activation function is used for the hidden layers and softmax activation function is used for the output layer. We use Adam optimizer \(^{28}\) and new-bob learning rate scheduler \(^{29}\) with initial learning rate of 0.0001 for training. The input of DNN is 23-band log Mel filterbank features with delta and delta-deltas and splicing with 5 context frames both left and right, giving 759 dimensions in total. Training process iterates over data samples in randomized order with mini-batch size of 256 samples. NNabla \(^{30}\) deep learning toolkit is used to implement DNN. Kaldi speech recognition toolkit \(^{31}\) is used to build Gaussian Mixture Model-HMM acoustic model, to produce forced senone level alignments of training data required for DNN-HMM training and to perform decoding with DNN-HMM required for WER evaluation. For decoding we also trained two 3-gram language models on the transcripts from the training data and on the CommonCrawl subset and interpolated them with SRILM toolkit \(^{32}\). The perplexity of the language model on our testing data set is 209.47.

Results of the baseline model trained on different data sets with different labels and tested on 15 hours of Italian SPEECON channel 4 are shown in Tab. 2. It is apparent from this table that decoding of noisy reverberated speech is a challenging task. While WER of the model trained on Channel 1 is incredibly high at 85.2\% due to significant distortions introduced to speech by environmental noises and reverberations in the testing noisy speech data, the model trained on Channel 4 achieves significantly lower WER by learning to normalize these distortions from the training data, and the model trained on Channels 1–4 results even better WER because of the generalized representations of clean and noisy data samples presenting in the training data. Our analysis of problematic utterances suggests that as the majority of the mistakes are made in „Spontaneous speech“, „Numbers, times, dates“ and „Named entities“ categories, where the language model could not be helpful.

An alternative to the proposed method would be to train a model on the target domain data and the labels produced by a first pass of unadapted model. As it follows from Tab. 2 this method does not seem to be practical in our setup, most likely because of extremely bad accuracy of the unadapted model. Moreover, the proposed method has an advantage of applicability in a crosslingual setup.

| System   | Training data | WER (%) |
|----------|---------------|---------|
| Baseline | Channel 1     | 85.2    |
| First pass | Channel 4    | 86.3    |
| Oracle   | Channel 4     | 51.8    |
| Oracle   | Channels 1–4  | 46.0    |

Table 2: Results of the baseline model.

3.3 Setup Description

Each of the experiments starts with DNN weights trained on 125 hours of clean close-talk Italian speech training data. Adaptation stage is performed on a combination of clean speech training data with senone labels and noisy speech adaptation data without senone labels (technically they all are set to 0). The domain classification sub-network is added at adaptation stage and consists of 2 hidden fully connected layers with 512 units each and the output layer with 2 outputs corresponding to the source and target domain classes in the adversarial task. Leaky ReLU activation function \(^{33}\) is used for the hidden layers and softmax activation function is used for the output layer. Input of domain classification sub-network is output of the \(f\)-th hidden layer of the main network (feature layer) passed through a Gradient Reversal Layer (GRL). GRL passes its input intact to its output during the forward pass and returns the inverted and scaled by \(\lambda\) gradient value from its output to its input during the backward pass. Adaptation procedure could be then interpreted as a regularizer of the DNN training. After it is finished, the domain classification sub-network is removed and decoding is performed as usual with the remaining DNN.

Three experiments are conducted to investigate the effectiveness of the proposed method. In the first experiment, we investigate the interaction between GRL coefficient \(\lambda\) and feature layer index \(f\) using 125 hours of channel 4 (middle/far distance microphone) as adaptation data. The best GRL coefficient \(\lambda\) and feature layer index \(f\) are then used for further experiments. The second experiment explores the impact of the adaptation data size on the final performance. In the third experiment, we perform a cross-lingual study when using the same amount of adaptation data but from French in order to examine importance of the language of adaptation data.

4 Results

4.1 Training Metrics

Fig. 2 shows the accuracy values for senone classification and domain discrimination during the adaptation stage. Training data set consists of equal proportions of Channel 1 and Channel 4 recordings and validation data set consists of equal proportions of Channels 1–4 recordings of Italian SPEECON corpus. Accuracy is defined as the number of correctly classified samples divided by the total number of samples. What stands out here is the markedly high accuracy of the domain classifier during the initial epochs, which suggests that the feature layer initially outputs quite distinct values for the clean and noisy speech. As the GRL coefficient is increased and the shared DNN parameters are adjusted towards more domain invariant representation, the accuracy of the domain classifier expectedly decreases and stabilizes slightly over the chance level around 55\%. At the same time, the senone classification accuracy first drops quite sharply in response to changes in how the feature layer represents the data and later recovers slowly due to the adaptation of the task specific layers to the new domain invariant output of the feature layer made possible by the utilization of the labeled clean speech data samples. Another interesting observation can be made by comparing the metrics of the domain classifier for the training and validation data sets. The performance of the domain classifier for the training and validation data sets aligns to similar
level after a few epochs of adaptation, which indicates that the representation learned by the shared DNN parameters does not just normalize seen data samples, but actually extracts only the information not related with recording conditions.

4.2 Effect of $\lambda$ and $f$

| $f$ | $\lambda = 1.0$ | $\lambda = 2.0$ | $\lambda = 4.0$ |
|-----|----------------|----------------|----------------|
| 1   | 84.5           | 78.7           | 76.8           |
| 2   | 70.2           | 69.0           |                |
| 3   | 69.8           | 69.2           | 74.5           |
| 4   | 71.9           | 71.5           | 74.9           |
| 5   | 74.1           | 74.7           | 75.6           |

Table 3: Results (WER in %) of adaptation on 125 hours of Channel 4.

First we use the fixed target domain data subset, namely 125 hours of Channel 4 recordings, to evaluate the effect of various combinations of the gradient reversal coefficient $\lambda$ and the feature layer index $f$. WER and relative error rate reduction (RERR) are listed in Tab. 3. The best combination is gradient reversal coefficient $\lambda = 2.0$ and feature layer index $f = 2$ and it results WER of 68.3%, which is within almost twice smaller gap with the best result of 46.0%, obtained by supervised training on Channels 1–4, compared to 85.2% resulted by unadapted model trained on Channel 1. In addition to that, we repeat the same experiment with Channels 2–4 as adaptation data, as the best baseline system also utilizes this data. We obtain WER of 66.6% and conclude that the gain in WER is too small in comparison to amount of additional adaptation data.

4.3 Effect of Adaptation Data

| Hours | WER (%) | RERR (%) |
|-------|---------|----------|
| 50    | 85.2    |          |
| 40    | 70.5    | 17.2     |
| 30    | 71.8    | 15.7     |
| 20    | 75.4    | 11.5     |
| 10    | 85.4    | -2.3     |
| 5     | 84.0    | 1.4      |

Table 4: Results of adaptation on Italian data with $f = 2$, $\lambda = 2.0$.

Next we use the best combination of the gradient reversal coefficient $\lambda$ and the feature layer index $f$ from the previous experiment to evaluate contribution of various amounts of adaptation data to accuracy of adapted model. Results are listed in Tab. 4. What emerges from the results reported here is that no significant drop in WER is observed if amount of adaptation data is decreased to 30 hours or one third of originally evaluated adaptation data set. On the one hand this finding suggests that one does not need to acquire large amount of the target domain data in order to get a moderate improvement of ASR system trained on clean speech data. On the other hand, it is possible that this effect of 30 hours of adaptation data is due to a good chance of having comparable number of distinct recording conditions in the adaptation and testing data and may not be generalizable to a larger testing data set with more diverse set of recording conditions.

4.4 Crosslingual Adaptation

We also run experiments on the same amounts of French data to see if it is important to use adaptation data for the same language as the language of interest. Results are listed in Tab. 5. Interestingly, the method improves WER even when used with the adaptation data for French while the language of interest is Italian. We also observe the same trend regarding amount of French adaptation data as with Italian adaptation data, namely insignificant contribution of additional adaptation data, besides 30 hours, to WER. Hence, it could conceivably be hypothesized that the method makes DNN more robust to a number of different recording conditions in general and not only to the recording conditions represented in the adaptation data.

| Hours | WER (%) | RERR (%) |
|-------|---------|----------|
| 50    | 84.2    |          |
| 40    | 74.5    | 12.6     |
| 30    | 75.6    | 11.3     |
| 20    | 80.2    | 5.9      |
| 10    | 83.7    | 1.8      |
| 5     | 84.4    | 0.9      |

Table 5: Results of adaptation on French data with $f = 2$, $\lambda = 2.0$.

5 Conclusions

The present study was designed to gain a better understanding of ability of unsupervised domain adaptation by adversarial Learning to improve robustness of ASR. We perform adaptation experiments on close-talk and far/middle distance recordings using the Italian and French SPEECON corpora. Our experimental results show that the proposed method improved significantly the WER in case of recording conditions mismatch without any transcriptions. Up to 19.8% relative WER improvement could be observed. Additionally, results on cross-lingual experiments also indicate that the usage of adaptation data from the same language is desirable, but not mandatory. Adaptation on French data resulted relative WER improvement up to 12.6%.

The present investigation has not considered more distant pairs of languages having smaller overlap in phonetic inventory, which is one of possible directions for the future research. Further work needs to be done to establish whether our conclusions would hold for more advanced DNN architectures, such as TDNN [34, 35], LSTM [36] and CNN [37], and training methods, such as Lattice-free MMI [38].
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