DNN Adaptation by Automatic Quality Estimation of ASR Hypotheses

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Abstract

In this paper we propose to exploit the automatic Quality Estimation (QE) of ASR hypotheses to perform the unsupervised adaptation of a deep neural network modeling acoustic probabilities. Our hypothesis is that significant improvements can be achieved by: \(i\) automatically transcribing the evaluation data we are currently trying to recognise, and \(ii\) selecting from it a subset of “good quality” instances based on the word error rate (WER) scores predicted by a QE component. To validate this hypothesis, we run several experiments on the evaluation data sets released for the CHiME-3 challenge. First, we operate in oracle conditions in which manual transcriptions of the evaluation data are available, thus allowing us to compute the \textit{true} sentence WER. In this scenario, we perform the adaptation with variable amounts of data, which are characterised by different levels of quality. Then, we move to realistic conditions in which the manual transcriptions of the evaluation data are not available. In this case, the adaptation is performed on data selected according to the WER scores \textit{predicted} by a QE component. Our results indicate that: \(i\) QE predictions allow us to closely approximate the adaptation results obtained in oracle conditions, and \(ii\) the overall ASR performance based on the proposed QE-driven adaptation method is significantly better than the strong, most recent, CHiME-3 baseline.

\textit{Keywords:} Deep neural networks, DNN adaptation, ASR quality estimation.

1. Introduction

Automatic speech recognition (ASR) with microphone arrays is gaining increasing interest in a variety of application scenarios, such as home and office automation, smart cars and humanoid robots. In such applications, ASR should be able to operate in environments

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where noises of various types, competing speakers and reverberation heavily affect recognition performance, which is usually satisfactory in controlled acoustic conditions. To cope with the above scenarios, most of the current approaches are based on the implementation of a variety of enhancement techniques such as beamforming, denoising and dereverberation [7].

The last CHiME challenge (CHiME-3\(^1\)) provided an excellent framework to evaluate signal enhancement approaches and noise-robust acoustic modelling techniques for ASR. Participants’ results\(^2\) evidenced the effectiveness of signal enhancement approaches, mostly based on “beamforming”, combined with the use of hybrid acoustic models based on deep neural networks hidden Markov models (DNN-HMMs)\(^1\).\(^2\).\(^3\). The effectiveness of acoustic modelling based on context-dependent DNN-HMMs was also demonstrated in several works dealing with applications spanning from mobile voice search\(^5\) to the transcription of broadcast news and YouTube videos\(^1\), conversational (at the telephone or in live scenarios) speech recognition\(^4\) and ASR in noisy environments\(^4\).

In [22], we observed a significant WER reduction on the CHiME-3 real test data by retraining the baseline DNN on the evaluation set itself and using the automatic transcriptions resulting from a first decoding pass to align acoustic observations with DNN outputs. After this “unsupervised” DNN retraining step (unsupervised as it relies on automatic transcriptions, which are not revised by a human) we achieved a WER reduction from 20.2% to 15.5%.\(^3\) These positive results motivate the research proposed in this work, which further explores unsupervised techniques for the “self” adaptation of a DNN (i.e. by tuning its parameters on the same test set we are currently trying to recognize) with an improved, automatically generated supervision. In particular, the full DNN retraining step adopted in [22] is now substituted by a more sophisticated solution, which enhances the adaptation with effective instance weighing and selection criteria.

At its core, our adaptation method is similar to the one described in [55], which adds to the objective function to optimize a regularization term based on the Kullback-Leibler divergence (KLD) between the original (non adapted) and the current DNN output distribution.\(^3\) However, departing from Yu et al.’s method, we explore different ways to enhance the process with automatic ASR quality predictions. In particular, building on the outcomes of previous research on automatic quality estimation for ASR\(^3\),\(^2\), we focus on two alternative solutions. The first one is based on weighing the KLD regularization term with coefficients that depend on the predicted quality of each transcribed sentence. The second one is based on filtering the adaptation set by removing the utterances that, in terms of predicted quality, seem to be less reliable.

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\(^1\)http://spandh.dcs.shef.ac.uk/chime_challenge/

\(^2\)This performance was achieved using filter-bank log-energies as acoustic features, as included in a previous CHiME-3 ASR baseline used in the competition held in 2015 (http://spandh.dcs.shef.ac.uk/chime_challenge/). A stronger baseline, which employs speaker normalized features, has been successively delivered. This baseline is the one used in the experiments documented in this paper.

\(^3\)The reason for choosing KLD regularization is that it can be implemented by constraining directly the target output DNN probabilities, making it possible to easily integrate the approach in the existing open-source ASR toolkits like KALDI\(^5\).
Our evaluation is carried out with the data sets released for the CHiME-3 challenge and with the most recent CHiME-3 baseline system. In a first round of experiments, we adapt the original DNN in cross conditions. In this setting, the manually transcribed development set is distinct from the evaluation set and it is used for a supervised DNN adaptation process. The available supervision allows us to compare the resulting performance with the results achieved when automatic (hence less accurate) transcriptions are used in place of the manual ones. With an oracle-based sentence selection (obtained by using the manual transcriptions as references to calculate the true sentence WER) we observe significant performance improvements when subsets of good quality adaptation instances are used instead of the whole data. This finding supports the intuition that automatic techniques to estimate transcription quality (e.g. by filtering out those with higher WER) can be used to inform the adaptation process and increase its robustness.

In the second round of experiments we switch to self DNN adaptation in homogeneous conditions, in which the adaptation is performed with automatic transcriptions of the same evaluation data we are currently trying to recognise (i.e. the real test set used in the CHiME-3 challenge). In this scenario we achieve the most interesting results, with a relative WER reduction of 11.7% (from 15.4% to 13.6%) obtained with the automatic sentence-level WER predictions returned by our ASR QE component. Besides this, another interesting result of our experiments is that the ASR performance gain achieved through self DNN adaptation has to be mostly attributed to the automatic selection of the adaptation utterances rather than to weighing the KLD regularization term, which has a limited effect on the overall performance. To complete our analysis, the usefulness of the proposed QE-based adaptation method is verified not only with filter-bank features, but also with feature normalization via maximum likelihood linear regression (fMLLR) transformations, which characterize the best performing systems in the CHiME-3 challenge \[20, 54\] as well as the most recent baseline. This is an interesting result since, while DNN adaptation has already proven to be effective with filter-bank features (see Section 2 for a review of DNN adaptation approaches), the benefits yielded by adaptation using acoustic features (speaker) normalized through fMLLR transformations are still questionable.

To the best of our knowledge, this paper represents the first investigation of the use of QE-based sentence selection for unsupervised DNN adaptation in the framework of ASR decoding. Overall, its main contributions include:

- A new application of the ASR QE procedure described in \[34\] to predict the WER of automatic transcription hypotheses;
- An extension of the KLD regularization approach for unsupervised DNN adaptation \[55\], which could be easily integrated in the KALDI speech recognition toolkit \[38\];
- Significant improvements over the strong, most recent CHiME-3 baseline.

All the experiments described in this paper have been carried out with the TranscRater open-source tool described in \[24\].
The paper is organized as follows. In Section 2 we summarize relevant previous works related to our research. In Section 3 we describe our approach to DNN adaptation. In Sections 4 and 5 we present the adopted automatic WER prediction method and the ASR system architectures. After the description of our experimental setup in Section 6, our results are presented in Section 7 and discussed in Section 8.

2. Related work

Detailed overviews about the CHiME challenges of years 2011 (CHiME-1), 2013 (CHiME-2) and 2015 (CHiME-3) can be respectively found in [6, 52, 5]. While the first round in 2011 was mostly focused on speech separation task, the last two editions addressed large vocabulary speech recognition in noisy environments. The last one, in particular, involved many participants addressing a variety of topics such as noise reduction, de-reverberation, speaker/noise adaptation, system combination and rescoring with long-spanning LMs. Our submission [22] mostly focused on three aspects: i) the automatic selection of the best channel, ii) DNN retraining and iii) rescoring of word lattices with a linear combination of 4-grams LMs and RNNLMs. As mentioned in the introduction, the significant improvements achieved with unsupervised DNN retraining motivated us to further investigate the DNN adaptation issue.

In the past, several adaptation techniques have been proposed for artificial neural networks employed in ASR hybrid systems. These are mostly based on the estimation of linear transformations of their input, output or hidden units [14, 1, 35, 28, 43]. Feature discriminative linear regression (fDLR) [40] and output-features discriminative linear regression (oDLR) [53] are other approaches specifically investigated for DNN adaptation. Regardless of the layer to which the transformation is applied, in all the mentioned approaches only the weights of the linear transformation are updated in order to optimize an objective function computed on the adaptation data. In this way, the probability that the DNN model overfits the adaptation data is reduced. Note that both fMLLR and fDLR are linear transformations applied to the input features; the difference between the two lies in the estimation criterion they adopt. fMLLR maximizes the likelihood of the adaptation observations, while fDLR optimizes a discriminative criterion computed on the same adaptation observation (e.g. it minimizes the mean squared error between target and actual output-state network distribution).

A variant of fDLR is described in [21], which proposes to adapt the DNN parameters within a maximum a posterior (MAP) framework. Basically, the method consists in adding to the objective function to optimize a term representing the prior density of the linear transformation weights. This approach demonstrated to be equivalent to L2 norm regularization [29] if the prior distribution of transformation weights is assumed to be Gaussian $\mathcal{N}(0, I)$. In general, adding a regularization term to the objective function proved to be effective to reduce model overfitting. An excellent review of “conservative training” approaches for artificial neural networks can be found in [2]. The use of a momentum term to update the DNN weights, the use of small values for the learning rate as well as of an early stopping criterion can be considered as adaptation methods.
In [55], the Kullback-Leibler divergence (KLD) between the original unadapted distribution of the DNN outputs and the related distribution estimated on the adaptation set is considered as regularization term. As reported in [55], this approach, also employed in our work, allowed obtaining significant WER reductions compared to fDLR transformation of the input features on two different tasks: voice search and lecture transcription. The weight assigned to the regularization term in the objective function is an important parameter to choose when using regularized learning.

The use of fMLLR features in combination with hybrid DNN-HMMs has been studied in [36]. On a private clean speech evaluation set, the authors observed that: i) filter-bank features and fMLLR features achieved comparable performance, and ii) only the combination of the two types of features, either at an early or late fusion stage, provided significant WER reductions. These results are somehow in contrast with those obtained in the CHiME-3 challenge, in which fMLLR normalization gives significant improvements compared to speaker-independent filter-bank features. However, we have to consider that participants in the CHiME-3 challenge experimented on noisy data and did not apply any automatic speaker diarization module, since both utterance segmentation and speaker labels were manually checked.

An approach for unsupervised speaker adaptation of DNNs using fMLLR features is also reported in [48]. The authors propose to train speaker-dependent amplitude parameters associated to hidden units of the network, obtaining significant performance improvements on the recognition of English TED talks.

In the context of speaker-adaptive training (SAT) via fMLLR [12], recently proposed approaches make use of i-vector [26] as speaker representation to perform acoustic feature normalization. In [32], an adaptation neural network is trained to convert i-vectors to speaker-dependent linear shifts which, in turn, are used to generate speaker-normalized features for SAT-DNN training/decoding. The work reported in [13] proposes to process HMM-based i-vectors with specific hidden layers of a DNN before combining them with hidden layers processing standard acoustic features. The work reported in [25] proposes to incorporate prior statistics (derived from gender clustering of training data) into i-vectors estimation, showing significant performance improvements when the approach is used for DNN adaptation of a hybrid ASR system.

The automatic selection of training data for acoustic modelling in speech recognition has been previously addressed in the context of lightly supervised training [27] and active learning approaches [18, 10]. The use of confidence measures for improving MLLR transformations has also been investigated in [37] in a German conversational speech recognition task. The authors showed significant WER reductions, for an ASR system based on a Gaussian Mixture Model (GMM), by removing the low confidence frames from the adaptation data. More recently, [49] proposed an automatic sentence selection method based on different types of confidence measures for the semi-supervised training of DNNs in a low-resource setting.

The use of QE as a quality prediction method alternative to confidence estimation is inspired by previous research on QE for machine translation [31, 44, 50, 45]. In the ASR field it has been first proposed in [34]. In such previous work, the objective was to by-
pass the dependency of confidence estimation on knowledge about the inner workings of the decoder that produces the transcriptions and, in turn, to avoid the risk of biased (often overestimated) quality estimates [9]. In [34] ASR QE is explored as a supervised regression problem in which the WER of an utterance transcription has to be automatically predicted. The extensive experiments in different testing conditions discussed in [34] indicate that regression models based on Extremely Randomized Trees (XRT) [15] can achieve competitive performance, being able to outperform strong baselines and to approximate the true WER scores computed against reference transcripts. In [46], our basic approach was refined in order to achieve robustness to large differences between training and test data. The proposed domain-adaptive approach based on multitask learning was intrinsically evaluated on multi-domain data, achieving good results both in regression and in classification mode. In order to explore the possible applications of ASR QE, in [23] we proposed its use for successfully improving hypothesis combination with ROVER [11]. Finally, in [24], we described TranscRater, our recently released open-source ASR QE tool. The tool is the one used for the experiments described in this paper.

3. KL-divergence based regularization

The DNNs considered in this work estimate the posterior probability of an output unit $s_i$ associated to a HMM output probability density function (PDF). The state posterior probability $p[s_i|o_t]$, being $o_t$ an observation at time $t$, is then converted into a PDF using the following Bayes formula:

$$p[o_t|s_i] = p[s_i|o_t] \frac{p[o_t]}{p[s_i]} \quad 1 \leq i \leq I \quad (1)$$

where $I$ is the total number of output PDFs and $p[o_t]$ is discarded since it does not depend on the state.

A possible criterion for estimating weights and biases of the DNN is to minimize over a training sample the cross-entropy $C(\hat{p}, p)$ between a target distribution $\hat{p}$ and the estimated one:

$$C(\hat{p}, p) = \frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{I} \hat{p}[s_i|o_t] \log p[s_i|o_t] \quad (2)$$

where $T$ is the total number of frames in the training utterances. Usually, the entries $\hat{p}[s_i|o_t]$ in the target distribution are obtained by forced alignment using an existing ASR system and assume the value of 1 over the aligned states.

The usual way to adapt a DNN trained on a large set of data (e.g. some thousands of hours of speech), given a much smaller set of adaptation data (e.g. some minutes of speech4), is to retrain the DNN over the adaptation set. This approach assumes that either manual or automatic transcriptions of the adaptation sentences are available but, due to

4Uttered by a new speaker or recorded in a new acoustic environment.
the small size of the adaptation set compared with the high number of parameters of the DNN model, it could happen that the model overfits the training data. As mentioned in the previous section, a solution to prevent overfitting effects is to adopt a conservative learning procedure, which can be implemented by adding a regularization component to the loss function to optimize.

In [55], the authors propose to use the Kullback-Leibler divergence between the original distribution and the adapted one as regularization term. Adding KLD computed on the adaptation set to cross-entropy (also evaluated on the adaptation set) results in the following objective function to minimize:

$$D(p, p) = (1 - \alpha)C(\hat{p}, p) + \alpha \frac{1}{N} \sum_{t=1}^{N} \sum_{i=1}^{I} \hat{p}[s_i|o_t] \log p[s_i|o_t]$$

(3)

where $N$ is the number of adaptation frames, $\hat{p}[s_i|o_t]$ is the posterior probability computed with the original DNN and $\alpha$ is the regularization coefficient. As reported in [55], Equation 3 can be rewritten as follows:

$$D(p, p) = \frac{1}{N} \sum_{t=1}^{N} \sum_{i=1}^{I} P[s_i|o_t] \log p[s_i|o_t]$$

(4)

where

$$P[s_i|o_t] = (1 - \alpha)\hat{p}[s_i|o_t] + \alpha \hat{p}[s_i|o_t], \quad 0 \leq \alpha \leq 1$$

(5)

Equation 4 states that KLD regularization can be implemented through cross-entropy minimization between a new target probability distribution $P$ and the current probability distribution $p$. The new target distribution is obtained as a linear interpolation of the original distribution $\hat{p}$ and the distribution $\hat{p}$ computed via forced alignment with the adaptation data. Note that, in Equation 5, a value of $\alpha = 0$ is equivalent to do a “pure” retraining of the DNN over the adaptation data (i.e. completely trusting them), while a value of $\alpha = 1$ means that the output probability distribution of the adapted DNN is forced to follow that of the original DNN (i.e. completely trusting the original model). Usually, the value of $\alpha$ is estimated on a development set, together with the value of the learning rate, and does not change across the test utterances. What one can expect is that the optimal value of $\alpha$ is close to 0 when the size of the adaptation set is large and the transcriptions of the adaptation sentences are not affected by errors (i.e. in supervised conditions). Otherwise, when the size of the adaptation set is small and/or its transcription can be affected by errors (i.e. in the case of unsupervised adaptation), the optimal value of $\alpha$ should increase.

It is worth remarking that the original DNN, producing the distribution $\hat{p}$ used in the above equations, could have been trained by optimizing a criterion different from cross-entropy minimization. This is actually the approach used in this study (see Section 5 for details on baseline DNN training).

Finally, unlike other methods, note that KLD-based regularization binds directly the DNN output probabilities rather than the model parameters. In this way, the method can be easily implemented with any software tool based on back-propagation (e.g. the KALDI toolkit), without introducing any modification.
3.1. Soft DNN adaptation

Experiments in [55] have shown a dependency of the optimal value of $\alpha$ in Equation 5 on the size of the adaptation data. However, as mentioned above, one could also expect that the optimal value of $\alpha$ depends on the quality of the supervision. Starting from this intuition, here we propose to compute $\alpha$ on a sentence basis, as a function of sentence WER estimates. To this end, we take advantage of previous research we conducted on ASR quality estimation (WER prediction) and word error detection.

In principle, we could simply use as sentence-dependent regularization coefficient the following value: $\alpha(k) = \text{WER}_{k}^{\text{pred}}, 1 \leq k \leq K$, where $0 \leq \text{WER}_{k}^{\text{pred}} \leq 1$ is an automatic estimate of the $k^{th}$ sentence WER and $K$ is the total number of adaptation sentences. However, note that in doing this if the value of $K$ is small and $\text{WER}_{k}^{\text{pred}} \approx 0$, the original distribution $\tilde{p}$, in Equation 5, is weighted by $\alpha \approx 0$ (i.e. we completely trust the adaptation data), augmenting the risk that the adapted DNN overfits the adaptation data. To avoid this effect we can simply add a bias to the sentence WER estimate as follows:

$$\alpha(k) = \beta + (1 - \beta) \times \text{WER}_{k}^{\text{pred}}, 1 \leq k \leq K, \quad 0 \leq \beta \leq 1$$

(6)

In the equation above, a value of $\beta = 0$ gives $\alpha(k) = \text{WER}_{k}^{\text{pred}}$, i.e. the regularization coefficient depends only on the sentence transcription quality. A value of $\beta = 1$ gives $\alpha(k) = \beta$, i.e. the regularization coefficient remains fixed over all adaptation sentences (this is the case of Equation 5). Therefore, optimizing over $\beta$ allows us to control the trade-off between the quality of the supervision and the size of the adaptation set.

We refer to the DNN adaptation method based on Equation 6 as a “soft” adaptation (in which the coefficients vary sentence by sentence), in contrast with the “hard” DNN adaptation approach based on Equation 5 (in which the coefficients are fixed).

4. ASR quality estimation

The simplest approach to roughly estimate transcription quality (without reference transcripts) is to consider sentence confidence scores, which describe how the system is certain about the quality of its own hypotheses. Sentence confidence scores can be computed by averaging the confidence of the words in the best output string. Such information, however, often reflects a biased perspective influenced by individual ASR decoder features.

Indeed, confidence scores are usually close to the maximum value, thus shifting the predicted WER (computed as $1 - \text{confidence}$) to scores that are close to zero.

To obtain more objective and reliable sentence-level WER predictions, in [34] we proposed ASR quality estimation as a supervised regression method that effectively exploits a combination of “glass-box” and “black-box” features. Glass-box features, similar to confidence scores, capture information inherent to the inner workings of the ASR system that produced the transcriptions. The black-box ones, instead, are extracted by looking only at the signal and the transcription. On one side, they try to capture the difficulty of transcribing the signal while, on the other side, they try to capture the plausibility of the output transcriptions. In both cases, the information used is independent from knowledge about
the ASR system, making ASR QE applicable to a wide range of scenarios in which the only elements available for quality prediction are the signal and the transcription.

In this paper, we trained XRT-based models \cite{15} with a combination of 41 ASR (glass-box) and textual (black-box) features. The ASR features are extracted from the confusion network (CN) \cite{30} derived from the word lattices generated by the ASR decoder (the one employed in this work is based on the KALDI toolkit \cite{38}), while the textual features are the same of \cite{34}. Table 1 provides the complete list of the features used. In our experiments, the regressors are respectively trained and tested on the CHiME-3 \textit{dt05\_real} and \textit{et05\_real} transcriptions described in Section 6.1. Their parameters, such as the number of bags, the number of trees per bag and the number of leaves per tree are tuned to minimize the mean absolute error (MAE) between the true and predicted WER scores using k-fold cross-validation on the \textit{dt05\_real} data.

### Table 1: Features (41 in total) for sentence-level WER prediction.

| **ASR (9)** | From each CN bin: the log of the first word posterior (1), the log of the first word posterior from the previous/next bin (2), the mean/std/min/max of the log posteriors in the bin (4), if the first word of the previous/next bin is silence (2) |
| **Sentence level (10)** | From each transcribed sentence: number of words (1), LM log probability (1), LM log probability of part of speech (POS) (1), log perplexity (1), LM log perplexity of POS (1), percentage (%) of numbers (1), % of tokens which do not contain only “[a-z]” (1), % of content words (1), % of nouns (1), % of verbs (1) |
| **Word level (22)** | From each transcribed word: Part-of-speech tag/score of the previous/current/next words (6), RNNLM probabilities given by models trained on in-domain/out-of-domain data (2), in-domain/out-of-domain 4-gram LM probability (2), number of phoneme classes including fricatives, liquids, nasals, stops and vowels (5), number of homophones (1), number of lexical neighbors (heteronyms) (1) binary features answering the three questions: “is the current word a stop word?”/“is the current word before/after repetition?”/“is the current word before/after silence?” (5) |

5. ASR system

The architecture of our ASR system is depicted in Figures 1 and 2. In the former one, it uses fMLLR normalized features; in the latter one, it uses filter-bank features. The system is mainly based on the KALDI CHiME-3 v2 package (derived from the ASR system described in \cite{20}) with the addition of a second decoding pass that performs unsupervised DNN adaptation as described in Section 3.

In our submission to CHiME-3 \cite{22}, we reached the best performance on the evaluation set, \textit{et05\_real}, with a simple delay-and-sum (DS) beamforming consisting in uniform weighting of the rephased signals of the 5 frontal microphones. A similar approach, although based on the well known BeamformIt toolkit \cite{4}, is also included in the recent software package implementing the CHiME-3 baseline. Hence, in order to comply with the baseline, for this work we used BeamformIt to implement signal enhancement.
After beamforming, both filter-bank and fMLLR features are computed and processed by a corresponding hybrid DNN-HMM system that produces the supervision for adapting the DNN in the final decoding pass.

5.1. Filter-bank features

The employed filter-bank consists of 40 log Mel scaled filters. Feature vectors are computed every 10ms by using a Hamming window of 25ms length and are mean/variance normalized on a speaker-by-speaker basis. The baseline DNN is trained using the Karel’s setup included in the KALDI toolkit. To this aim the 8,738 training utterances were aligned to their transcriptions by means of the baseline GMM-HMM models. An 11-frame context window (5 frames on each side) is used as input to form a 440 dimensional feature.

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5 The initial GMM system makes use of the KALDI recipe associated to the earlier CHiME challenges.
vector. The DNN has 7 hidden layers, each with 2,048 neurons. The DNN is trained in several stages including Restricted Boltzmann Machines (RBM) pre-training, mini-batch stochastic gradient descent training, and sequence-discriminative training using state-level Minimum Bayes Risk (sMBR). Initially, the learning rate is set to 0.008 and it is halved every time the relative difference in frame accuracy between two epochs on a cross-validation set falls below 0.5%. A frame accuracy improvement on the cross-validation set lower than 0.1% stops the optimization. All experiments involving adaptation of the baseline DNN, aimed at minimizing the objective function defined in Equation 4, are performed according to the above recipe.

5.2. fMLLR features

For training, 13 mel-frequency cepstral coefficients (MFCCs) are computed every 10 ms by using a Hamming window of 25 ms length. These features are mean/variance normalized on a speaker-by-speaker basis, spliced by +/- 3 frames next to the central frame and projected down to 40 dimensions using linear discriminant analysis (LDA) and maximum likelihood linear transformation (MLLT) \[38\]. Then, a single speaker-dependent fMLLR transform is estimated and applied for speaker adaptive training of triphone HMM-GMMs. The DNN-HMMs hybrid systems are built on top of LDA+MLLT+fMLLR features and SAT triphone HMM-GMMs.

During decoding, first LDA+MLTT+fMLLR are derived using auxiliary HMM-GMMs. To this end, a preliminary decoding pass with speaker-independent (SI) HMM-GMM is conducted to produce a word lattice for each input utterance. Then, a single fMLLR transform for each speaker is estimated from sufficient statistics collected from SI word lattices in order to maximize the likelihood of the acoustic observations given the SAT triphone HMM-GMMs. These transforms are used with SAT triphone HMM-GMMs to produce new word lattices. A second set of fMLLR transforms is estimated from new word lattices and combined with the first set of transforms. Finally, the resulting transforms are applied to normalize the features processed by the DNN-HMM hybrid system in the first decoding pass of Figure 1. The training of the corresponding baseline DNN, as well as DNN adaptation by KLD regularization, use the recipe adopted for filter-bank features.

5.3. Language models

The LM employed in the experiments is the 3-gram LM provided with the CHiME-3 v2 package release, which uses the Kneser-Ney smoothing method for estimating back-off probabilities. It was trained with around 37 million words. After pruning low frequency words, the vocabulary size is approximately 5,000 words and the perplexity value (measured over \texttt{dt05\_real} reference transcriptions) is 119.2.

Finally, although not depicted in the figure, we also run a final rescore of the n-best lists generated in the second decoding pass with the 5-gram LM and the RNNLM included in the CHiME-3 v2 package.
6. Experimental setup

6.1. Speech corpora

For our experiments, we use the multiple-microphone evaluation data collected for the CHiME-3 challenge, which is publicly available\footnote{\url{http://spandh.dcs.shef.ac.uk/chime_challenge/download.html}}. Complete details about this data set, the overall challenge and its outcomes can be found in the related overview paper\footnote{\url{http://spandh.dcs.shef.ac.uk/chime_challenge/download.html}}, which also reports the performance of the 26 participating systems.

Six different microphones, placed on a tablet PC, were used to record sentences of the Wall Street Journal (WSJ) corpus, uttered by different speakers in four different environments (bus, cafe, pedestrian area and street junction). The training corpus consists of 1,600 “real” noisy sentences uttered by 4 speakers, and of 7,138 “simulated” noisy sentences uttered by 83 speakers forming the WSJ SI-84 training set. Simulated noisy sentences are generated by means of convolution of clean signals with impulse responses of the above mentioned environments and summing the corresponding pre-recorded background noises.

Two evaluation corpora were collected in this scenario: the $dt05_{\text{real}}$ development set, formed by 1,640 sentences uttered by 4 different speakers, and the $et05_{\text{real}}$ test set, formed by 1,320 utterances acquired from 4 other speakers. In addition, two parallel sets of “simulated” noisy utterances (namely $dt05_{\text{simu}}$ and $et05_{\text{simu}}$) were generated as previously described. There is no speaker overlap between training, development and test sets. The number of utterances in the evaluation corpora is equally distributed among speakers and types of noise, that is, every speaker uttered the same number of sentences in each of the four environments. In both training and evaluation data sets, utterance segmentation was manually checked and the corresponding speaker identity was annotated. Therefore, no automatic speaker diarization module was employed in the experiments. Table 2 shows some statistics of the CHiME-3 training, $real$ development and test sets (the corresponding simulated development and test sets exhibit the same statistics of the $real$ data).

|     | tr05_simu | tr05_real | dt05_real | et05_real |
|-----|-----------|-----------|-----------|-----------|
| duration | 15h9m | 2h54m | 2h16m | 1h50m |
| # sentences | 7,138 | 1,600 | 1,640 | 1,320 |
| # words | 136.5k | 28.3k | 27.1k | 21.4k |
| dict. size | 8.9k | 5.6k | 1.6k | 1.3k |
| # speakers | 83 | 4 | 4 | 4 |
| # noises | 4 | 4 | 4 | 4 |

Table 2: Statistics of CHiME-3 training, real development and real test audio data.

6.2. Experiment definition

All the experiments were conducted on the “real” subsets of the CHiME-3 evaluation data: $dt05_{\text{real}}$ and $et05_{\text{real}}$. For brevity, henceforth we will respectively refer to them
as DT05 and ET05. We report performance for ASR systems employing both fMLLR normalized features (Figure 1) and filter-bank features (Figure 2). ASR parameters (LM weight, α and β coefficients in Equations 5 and 6 respectively) are tuned on the development set DT05.

The soft adaptation approach described in Section 3 was applied in both “oracle” and “predicted” conditions. Oracle WER scores (oWER henceforth) are computed from reference transcriptions, while predicted WER scores (pWER) are estimated by the ASR QE system described in Section 4. Both values are used as WER estimates in Equation 6 to compute the target probability distribution. The performance achieved by oracle sentence WER represents the upper bound of the soft adaptation approach.

The QE model used for WER prediction is trained and optimized on the development set. The XRT parameters are tuned in 8-fold cross validation, minimizing the mean absolute error (MAE) between the predicted and the true WER. The partitioning is done to avoid speaker or sentence overlaps between training and test folds.

Table 3 gives the complete list of DNN adaptation experiments we performed. Each experiment is identified by: i) a combination of adaptation/evaluation sets, ii) the supervision used (manual or automatic), and iii) the features employed (filter-bank or fMLLR normalized). For instance, the experiment named DT05+man+fMLLR+ET05 in the first row of the table indicates that the baseline DNN is adapted using DT05 as adaptation set, the manual supervision, fMLLR features and the evaluation set is ET05.

| cross conditions | adaptation set | type of supervision | features type | evaluation set |
|------------------|----------------|---------------------|--------------|---------------|
| DT05+man+fMLLR+ET05 | DT05 | manual | fMLLR | ET05 |
| DT05+man+fbank+ET05 | DT05 | manual | filter-bank | ET05 |
| DT05+auto+fMLLR+ET05 | DT05 | automatic | fMLLR | ET05 |
| DT05+auto+fbank+ET05 | DT05 | automatic | filter-bank | ET05 |

| homogeneous conditions | | | | |
|-------------------------|-----------------|-----------------|-----------------|
| DT05+auto+fMLLR+DT05 | DT05 | automatic | fMLLR | DT05 |
| DT05+auto+fbank+DT05 | DT05 | automatic | filter-bank | DT05 |
| ET05+auto+fMLLR+ET05 | ET05 | automatic | fMLLR | ET05 |
| ET05+auto+fbank+ET05 | ET05 | automatic | filter-bank | ET05 |

Table 3: List of DNN adaptation experiments.

The table is divided in two parts, respectively describing experiments carried out in cross and homogeneous conditions. In cross conditions (first four rows), the adaptation and evaluation sets are distinct. Here, our goal is to compare performance by varying the type of supervision (manual or automatic) of the adaptation data and, in case the automatic supervision is used, by varying the size of the adaptation set according to its quality. In homogeneous conditions (last four rows), the adaptation set coincides with the evaluation
set. In this case, our goal is to compare performance achieved by selecting adaptation sets with different levels of quality.

Note that DNN adaptation with manual supervision (first two rows of Table 3) is only meaningful in cross conditions, since we assume it is not available for the evaluation set ET05. The automatic supervisions of the adaptation sets (i.e DT05 or ET05, depending on the experiment type) are produced by the first decoding passes of the ASR systems depicted in Figures 1 and 2. KLD regularization with manual supervision is applied according to Equation 5. Instead, with automatic supervision, both hard (based on Equation 5) and soft (based on Equation 6) DNN adaptation approaches are applied.

Furthermore, it’s worth observing that the cross-condition situation fits an “offline” application scenario, where a DNN can be adapted using data and corresponding automatic transcriptions collected on the field during the ASR system working. In a successive phase, the adapted DNN can be loaded into the ASR system itself.

Finally, as mentioned in Section 1, and as it will be shown below, top performance is achieved by properly selecting subsets of the adaptation data. Therefore, similarly to the other tuning parameters, the optimal selection thresholds used to estimate the final performance are computed on the development set DT05.

7. Results

In this section we present the experimental results obtained in the different settings outlined in Table 3, playing with: i) the different conditions, ii) the type of supervision, iii) the size of the adaptation data and iv) the way the adaptation data is selected.

In the analysis and in the subsequent discussion, our WER scores are not compared against those achieved by the best ASR system participating in the CHiME-3 challenge [54], which uses a far more complex architecture for signal pre-processing and cross system combination, as well as an augmented set of training data. Indeed, implementing such a state-of-the-art system was out of the scope of this work, whose objective is to show the effectiveness of QE-based DNN adaptation to improve the performance of a standard, less complex but still strong ASR system. For this reason, our term of comparison is represented by the reference CHiME-3 baseline, which results in 15.4% WER on ET05 and 8.2% WER on DT05. Despite the generality of the proposed approach, integrating our method in a state-of-the-art ASR system like the one described in [54] and quantify the performance gains yielded by QE-based DNN adaptation is left as a possible direction for future work.

7.1. DNN adaptation in cross conditions

In this section we analyse the performance achieved in cross conditions, both with manual and automatic supervision. First, we use all the sentences in DT05 for adapting the DNN. Then, we show the performance achieved with the automatic supervision provided by adaptation data derived from DT05 after removing the utterances with the highest WER.
7.1.1. Using all the adaptation utterances

Figure 3a shows the WERs (as functions of the regularization coefficient \( \alpha \) in Equation \( 5 \)) achieved on the evaluation set ET05 by using fMLLR features both with manual and automatic supervision. In a similar way, the performance reached with filter-bank features is given in Figure 3b. The horizontal line in both the figures corresponds to the baseline performance.

![Figure 3a](image1.png)

(a)

![Figure 3b](image2.png)

(b)

Figure 3: WER achieved on evaluation set ET05 as a function of the regularization coefficient \( \alpha \), using DT05 as adaptation set.

As can be seen, the use of manual supervision, or equivalently the supervised adaptation, allows to improve baseline performance with both types of features. In both cases, there is an intermediate optimal value of \( \alpha \) in the interval \([0, 1]\), indicating that we should not totally trust neither the original model nor the adaptation data. With the best value, we gain about 1\% WER point, indicating the efficacy of the interpolation procedure expressed by Equation \( 5 \).

Note the substantial performance reduction in Figure 3b at \( \alpha = 0 \) (both for supervised and unsupervised adaptation), suggesting that a data overfitting effect has probably occurred. The same behavior is not observed with supervised adaptation using fMLLR features (Figure 3a), where at \( \alpha = 0 \) no significant performance degradation is observed. This result can be explained by considering that fMLLR transformations already reduce the acoustic mismatch between adaptation (DT05) and evaluation (ET05) sets. This is confirmed by the fact that, in Figure 3b, the curve labelled DT05+man+fbank+ET05 is shifted towards the right part of the graph more than the corresponding curve DT05+man+fMLLR+ET05.

As explained in Section 3, a value of \( \alpha = 0 \) corresponds to completely ignoring the contribution of the original DNN output distribution in the construction of the cross-entropy function (i.e. we completely trust the adaptation data), while a value \( \alpha = 1 \) forces the DNN parameters to follow those of the original distribution (i.e. we completely trust the original model).
in Figure 3a, meaning that the adaptation procedure trusts the fMLLR normalized features more than the filter-bank ones. Referring to the same Figure 3a, data overfitting (at $\alpha = 0$) instead occurs with unsupervised adaptation, as if the errors in the supervision acted similarly to an acoustic mismatch between adaptation and evaluation sets. Based on these outcomes, we decided to investigate the effects of reducing the errors in the automatic transcription.

7.1.2. Selecting adaptation utterances

To check the possible impact of automatic transcription errors in the supervision, we extracted from the adaptation set $DT05$ the utterances whose true WER, computed from the reference transcriptions, is lower than 10%. Then, we adapted the baseline DNN with the hard approach and by varying the value of the regularization coefficient $\alpha$. The results are shown in Figures 4a and 4b. For comparison purposes, the two figures also include the same curves of Figures 3a and 3b related to the use of the whole adaptation set. As can be seen, the selection of adaptation utterances with $\text{WER} < 10\%$ produces curves that approach those obtained using manual supervision, showing the benefits of reducing the transcription errors in the supervision.

![Figure 4: WER achieved on evaluation set ET05 as a function of the regularization coefficient $\alpha$, using as adaptation set the subset of $DT05$ with oWER $\leq 10\%$.](image)

7.2. DNN adaptation in homogeneous conditions

In this section we report and discuss the performance achieved in homogeneous conditions with automatic supervision. First, we use the whole available set of adaptation utterances. Then, by applying ASR QE for WER prediction, we experiment with different subsets of the data selected according to their estimated quality.
7.2.1. Using all the adaptation utterances

The experiments were conducted by performing two decoding passes, as explained in Section 5. The transcriptions resulting from the first pass, based on the baseline DNNs, provide the supervision for the following adaptation steps. Then, the adapted DNNs are exploited in the second decoding pass to produce the final transcriptions. Performance results achieved on both development and evaluation sets, with hard and soft adaptation, are given in Table 4 (in parentheses, we show the absolute WER reduction with respect to baseline performance). In the case of soft adaptation, both oracle and automatically-predicted sentence WERs were tested. Similarly to the experiments in Figure 3, we measured performance as a function of the coefficient $\alpha$. We also carried out the same set of experiments evaluating performance also as function of coefficient $\beta$ defined in Equation 6. However, for reasons of compactness, we do not provide the whole set of results and Table 4 only refers to the top WER values achieved.

First of all, differently from the performance shown in Figures 3a and 3b, experiments in homogeneous conditions do not exhibit clear minimum values of the corresponding WER. Basically, no significant WER variations are observed for both $\alpha$ and $\beta$ coefficients ranging in the interval $[0.0 - 0.7]$. The best performance is achieved for $\alpha = \beta = 0.7$, while for $(\alpha, \beta) > 0.7$ the WERs increase.

In Table 4 it is worth noting the significant WER reductions, compared to baseline performance, yielded by filter-bank features on both DT05 and ET05. Although similar performance gains are not observed with fMLLR features, especially on DT05 (as just pointed out above, probably due to their capability of reducing the acoustic mismatch between training and testing conditions), these results confirm the effectiveness of the two-pass decoding method. Note also that no substantial advantages are brought by the soft adaptation approach compared to the hard one. Despite this fact, it is worth observing the very close

| experiment code       | HARD (oWER) adaptation | SOFT (pWER) adaptation |
|-----------------------|------------------------|------------------------|
| DT05+auto+fMLLR+DT05  | 8.0(0.2)               | 7.9(0.3)               | 8.0(0.2)               |
| DT05+auto+fbank+DT05  | 9.5(1.6)               | 9.2(1.9)               | 9.3(1.8)               |
| ET05+auto+fMLLR+ET05  | 14.5(0.9)              | 14.3(1.1)              | 14.4(1.0)              |
| ET05+auto+fbank+ET05  | 17.7(3.2)              | 17.1(3.8)              | 17.6(3.3)              |

Table 4: %WER achieved by unsupervised DNN adaptation in homogeneous conditions.
performance between oracle and predicted WER estimates, which demonstrates the efficacy
of the proposed ASR QE approach.

In summary, what one can learn from the experiments discussed so far is that: i) DNN
adaptation in homogeneous conditions with two passes of decoding, using the whole set of
adaptation utterances, yields performance improvements, ii) automatic utterance selection
based on oracle WER values is effective in cross conditions suggesting, together with the
outcome above, to repeat the corresponding experiment in homogeneous conditions and
using ASR QE, and iii) no significant performance gain can be achieved with the soft
adaptation method based on Equation 6. The latter result suggests to investigate measures
for expressing sentence quality that are alternative to sentence WER used in Equation 6. In
addition, weighing of output probabilities in Equation 5, could be applied at a granularity
level higher than that of the sentence, e.g. at the level of word or even of single frame.
Though interesting, a formal verification of these hypotheses is out of the scope of this
paper and is left for future work.

Figure 5: WER achieved with oracle (oWER) and ASR QE (pWER) selection of adaptation
utterances, on the development set DT05, as functions of the regularization coefficient $\alpha$.

### 7.2.2. Selecting adaptation utterances

For conciseness, in the next set of experiments we report performance results only for
fMLLR normalized features, since they are the most effective ones. However, the same
and even more evident trends, were also observed using filter-bank features. Figures 5a
and 5b report the performance achieved on DT05 using subsets of adaptation utterances of
different size. The utterances of the development set DT05 were sorted according to the
WER resulting from the first decoding pass. For sorting, we used both oracle WER values
and WER predictions obtained with the ASR QE approach described in Section 4. We extracted from DT05 four adaptation sets, respectively containing the “best” 300, 600, 900 and 1,200 utterances. The various subsets, together with their automatic transcriptions, were used to adapt the baseline DNN by means of the hard approach. The reason for putting thresholds to the size of the adaptation set to compute our results lies in the fact that we want to do a fair comparison between the two selection methods adopted (oWER and pWER). In fact, sentence selection according to a preassigned WER threshold produces unbalanced adaptation sets of different sizes in correspondence to the application of each of the two methods. Figures 6a and 6b were derived, similarly to Figures 5a and 5b, from the evaluation corpus ET05.

From the above figures, it is evident the efficacy of using only subsets of mid-high quality transcriptions for adapting the DNNs employed in the second decoding pass. Indeed, in each figure the minimum WER is reached with a couple of optimal values of the pair: (α, K), where K is the size of the adaptation set. This value is 900 for DT05 (Figures 6a and 6b) and 600 for ET05 (Figures 5a and 5b). The total improvement with respect to i) the baseline performance and ii) the performance achieved using the whole set of adaptation utterances is remarkable. The difference in the optimal values of K for DT05 and ET05 is probably due to the different size of the two corpora (DT05 contains 1,640 utterances, ET05 contains 1,320 utterances). Unsurprisingly, the performance achieved with the ASR QE approach is lower than the upper-bound results obtained with oracle WER estimates. However, especially on the evaluation corpus ET05, the improvements over the baseline are considerable.

Note that, in all figures, the optimal values of α result to be quite low, ranging in the
interval $[0.1 - 0.3]$. This indicates that the regularization term contributes to a small extent to the reduction of the overall WER. Consequently, the performance improvements resulting after utterance selection can be mostly attributed to the better quality of the adaptation set (the adaptation method trusts adaptation sets that now include only “good” sentences) rather than to the use of KLD regularization.

Although for comparison purposes our analysis focused on the size of the adaptation set to perform sentence selection, in real applications it is more feasible to select sentences on the basis of their predicted WER. Therefore, the next set of experiments was carried out by putting selection thresholds on sentence ASR QE predictions. Figure 7a shows the performance achieved on the $DT05$ corpus with hard DNN adaptation as a function of the $\alpha$ coefficient, varying the thresholds applied to $oWER$ values to select the adaptation utterances. Figure 7b, instead, shows the performance reached when $pWER$ estimates are employed. Also in this case, the performance improvements with respect to the baseline, with both $oWER$ and $pWER$ are evident. The optimal values for the pair $oWER_{thr}, \alpha$ (Figure 7a) resulted to be $oWER_{thr} = 10\%$, $\alpha = 0.1$, where $oWER_{thr}$ indicates the selection threshold. Similarly, using $pWER$ estimates the corresponding optimal values are $pWER_{thr} = 10\%$, $\alpha = 0.3$. With $pWER$, the higher value for $\alpha$ compared to the value resulting from the use of the $oWER$ ($\alpha = 0.1$) approach is probably due to errors in the automatic WER predictions that have to be compensated.

Table 5 gives the final performance achieved on both $DT05$ and $ET05$ using the two-pass decoding approach and the automatic selection of adaptation utterances by means of automatically predicted WERs. For both sets, the optimal values of the pairs $(\alpha, WER_{thr})$
are those estimated on the DT05 development corpus, i.e. ($\alpha = 0.1$, $o\text{WER}_{\text{thr}} = 10\%$) and ($\alpha = 0.3$, $p\text{WER}_{\text{thr}} = 10\%$).

|            | DT05 | ET05 |
|------------|------|------|
|            | fMLLR | fbank | fMLLR | fbank |
| baseline   | 8.2   | 11.1  | 15.4  | 20.9  |
| oWER       | 7.1   | 7.7   | 12.4  | 14.2  |
| pWER       | 7.5   | 8.3   | 13.6  | 15.0  |

Table 5: %WER achieved in homogeneous conditions using the optimal parameter pairs ($\alpha$, $\text{WER}_{\text{thr}}$) estimated on DT05.

Table 5 confirms the effectiveness of the proposed two-pass, QE-based adaptation approach when QE parameter optimization is carried out on the development set. In the table it can be noticed that, although filter-bank features exhibit higher WER than the fMLLR normalized ones, after the unsupervised adaptation procedure the performance gap is significantly reduced (less than 2% absolute WER on ET05). In all cases, the small differences between the performance yielded by the use of oracle and the corresponding predicted WERs is noteworthy.

The results in Table 5 are noticeable, considering that they outperform those given by a strong ASR baseline, implemented with state-of-the-art ASR technologies, i.e.: BeamformIt for speech enhancement, hybrid DNN-HMMs for acoustic modeling and speaker-dependent fMLLR transformations for acoustic model adaptation.

### 7.2.3. LM rescoring

Table 6 illustrates the results achieved on ET05 with the LM rescoring procedure released in the updated CHiME-3 recipe. This procedure rescores the final word lattices produced in the second decoding pass by two consecutive steps: first by using a 5-grams LM, then by means of a linear combination of a 5-grams LM and a RNNLM.

|            | 3-gram | 5-gram | RNNLM |
|------------|--------|--------|-------|
| oWER       | 12.4   | 10.8   | 9.9   |
| pWER       | 13.6   | 11.9   | 10.9  |

Table 6: %WER achieved, in homogeneous conditions on ET05, with automatic data selection and using the baseline LM rescoring passes (see [20]).

The significant performance gains demonstrate the additive effect of LM rescoring over DNN adaptation, allowing us to reach a significant 10.9% WER on ET05.\[10\]

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\[10\] See [http://spandh.dcs.shef.ac.uk/chime_challenge/results.html](http://spandh.dcs.shef.ac.uk/chime_challenge/results.html) for the official results of the challenge.
8. Discussion

The results achieved so far allow us to claim that, regardless of the type of acoustic features employed in the experiments (filter-bank or fMLLR normalized):

a) The benefits yielded by KLD-based regularization, compared with DNN retraining without any regularization, are limited. This is probably due to the fact that the size of the adaptation sets considered in our experiments is large enough to prevent data overfitting (actually, previous research on KLD regularization [53] demonstrates its effectiveness using only few minutes of adaptation data);

b) The presence of errors in the automatic transcription of the adaptation data is detrimental, especially when DNN adaptation is carried out in homogeneous conditions. In fact, comparing the results in the last two rows of Table 4 (achieved by using the whole ET05 corpus as adaptation set) with those in Table 5 (obtained by using a subset of adaptation utterances with “few” transcription errors) we notice, in oracle conditions, absolute WER reductions of around 2% with fMLLR and 4% with filter-bank features. Coherent WER reductions of around 1% and 3% are also achieved when applying our ASR QE-based selection method. This demonstrates the effectiveness of the proposed QE-informed approach for DNN adaptation.

It is worth pointing out that, till now, we have only considered KLD regularization for implementing DNN adaptation. However, as mentioned in Section 2, several previous works proposed alternative approaches based on the use of a single linear transformation, which can be applied either to the input or the output layer of the network. Therefore, in order to assess the effectiveness and the general applicability of the proposed QE-based approach, we also experimented with the output-feature discriminative linear regression (oDLR) transformation, in a way similar to that described in [53]. The results obtained in homogeneous conditions, both with and without ASR QE, are given in Table 7 (for comparison purposes, the baseline performance is also reported in the table). Similarly to results shown in Table 4 the optimal thresholds for both oracle and predicted sentence WER values are empirically estimated on DT05. The resulting values for \( o\text{WER}_{thr} \) and \( p\text{WER}_{thr} \) are respectively 10% and 20%.

|                | DT05 | ET05 |
|----------------|------|------|
|                | fMLLR | fbank | fMLLR | fbank |
| baseline       | 8.2   | 11.1  | 15.4  | 20.9  |
| oDLR           | 7.9   | 9.6   | 13.8  | 17.5  |
| oDLR+oWER      | 7.4   | 9.2   | 13.0  | 16.8  |
| oDLR+pWER      | 7.7   | 9.5   | 13.6  | 17.2  |

Table 7: %WER achieved in homogeneous conditions with oDLR-based adaptation, without using ASR QE (oDLR), using utterance selection based on oracle WERs (oDLR+oWER) and on predicted WERs (oDLR+pWER).
As shown in the table, the use of oDLR alone (even without ASR QE) always results in noticeable improvements over the baseline. The considerable WER reductions measured in oracle conditions (oDLR+oWER), however, indicate the high potential of a QE-driven selection of the adaptation utterances also with this simple DNN adaptation method. In general, the performance improvements are smaller than the corresponding results for KLD regularization reported in Table 5. Such lower results can be explained by the findings reported in [16], in which the authors compared approaches based on MLLR and maximum a posterior probability (MAP) for GMM-HMMs adaptation. In this case, the impact of errors in the supervision is directly proportional to the number of transformation parameters to estimate. Indeed, while in the experiments reported in Section 7 all the parameters of the original DNN are adapted, with oDLR only a small fraction of them (around 13%) is updated. The reduced sensitivity to errors in the supervision is also reflected by the higher value of the threshold used to select the adaptation data (20% for oDLR vs 10% for KLD).

The results measured in oracle conditions suggest a higher potential for the application of QE to KLD-based regularization rather than to oDLR. This intuition, however, is partially contradicted by the last row of Table 5 (oDLR+pWER). With predicted WER scores, indeed, the values achieved with fMLLR are only slightly worse or identical to those in Table 5. To put into perspective this unexpected “exception” in the results, it’s worth remarking that the impact of QE in DNN adaptation is proportional to the acoustic mismatch between training and test data. As observed in Sections 7.1.1 and 7.2.1, fMLLR features have the capability to reduce such mismatch, making the gains brought by QE-based adaptation less evident than those achieved with filter-bank. In light of this, although on ET05 and with fMLLR features oDLR is competitive with the more complex KLD-based regularization proposed in this paper, we believe that more challenging data (featuring a higher mismatch between training and test) would increase the distance between the two approaches and reward our method. A comparison between different DNN adaptation methods across multiple data sets featuring variable degrees of acoustic mismatch is definitely an interesting direction for future research.

9. Conclusions

In this paper, we proposed to exploit automatic Quality Estimation (QE) of ASR hypotheses to perform the unsupervised adaptation of a deep neural network modeling acoustic probabilities. We developed our approach motivated by the two following hypotheses:

1. The adaptation process does not necessarily require the supervision of a manually-transcribed development set. Manual supervision can be replaced by a two-pass decoding procedure, in which the evaluation data we are currently trying to recognise are automatically transcribed and used to inform the adaptation process;
2. The whole process can benefit from methods that take into account the quality of the supervision. In particular, automatic quality predictions can be used either to weigh the adaptation instances or to discard the less reliable ones.
To implement our approach, we retrained a (baseline) DNN by minimizing an objective function defined by a linear combination of the usual cross-entropy measure (evaluated on a given adaptation set) and a regularization term. This is the Kullback-Leibler divergence between the output distribution of the original DNN and the actual output distribution.

First, we experimented in “cross conditions”, by adapting on the real development set of the CHiME-3 challenge and testing on the corresponding real evaluation set. In this scenario, we found that, when using all the manually-transcribed adaptation data, the KLD-based approach is effective. Then, moving to the automatically-generated supervision of the adaptation data, we discovered a correlation between performance results and the quality of the adaptation data. In particular, in “oracle” conditions (i.e. with true WER scores), DNN adaptation benefits from removing utterances with a WER score above a given threshold.

Building on this result, we focused on “self” DNN adaptation in “homogeneous conditions”, in which the baseline DNN is adapted on the same evaluation set (ET05) by exploiting the automatic supervision derived from a first ASR decoding pass. Similarly to the cross-condition scenario, this approach allowed us to significantly improve the performance when “low quality” sentences (i.e. sentences that exhibit oracle WERs higher than an optimal threshold) are removed from the adaptation set. Improvements were measured not only in “oracle” conditions (i.e. with true WER scores), but also in realistic conditions in which manual references are not available and the only viable solution is to rely upon predicted WERs. To this aim, building on previous positive results on quality estimation for ASR [34, 46, 23], we used automatic WER prediction as a criterion to isolate subsets of the adaptation data featuring variable quality. The results of an extensive set of experiments allowed us to conclude that:

- Exploiting ASR QE for DNN adaptation in a two-pass decoding architecture yields significant performance improvements over the strong, most recent CHiME-3 baseline;
- Self DNN adaptation is more effective with filter-bank acoustic features than with fMLLR normalized features. This behavior is probably due to the smaller mismatch between training and test data caused by the use of fMLLR transformations, indicating a higher potential of the QE-driven approach in a scenario characterized by weakness of fMLLR in reducing such mismatch (e.g. with small adaptation sets);
- ASR QE is less effective with output discriminative linear regression (oDLR) transformation for DNN adaptation, due to the lower number of parameters to adapt compared to KLD regularization. This demonstrates the portability of our method, but a higher effectiveness with large DNNs.

Finally, we applied the LM rescoring procedure delivered with the CHiME-3 baseline to the word lattices produced after the second, DNN-adapted, decoding pass. The resulting WER reductions demonstrate the independent effects of LM rescoring and the proposed DNN adaptation approach. Our full-fledged system for DNN adaptation, integrating KLD and ASR QE for data selection, allows us to outperform the strong CHiME-3 baseline with a 1.7% WER reduction (from 12.6% to 10.9%).
Some interesting directions for future work already emerged in the course of this research. One is to further explore the portability of the proposed ASR QE approach, by integrating it into other state-of-the-art ASR systems. To validate our working hypotheses, in this paper we started from the strong CHiME-3 baseline; now it would be interesting to test its effectiveness within more powerful DNNs (e.g. capable of modeling time dependencies among acoustic observations, such as bidirectional recurrent neural networks \cite{17,3}) having a higher number of parameters to adapt. Another interesting direction is to investigate ways to express hypotheses’ quality at a granularity level higher than that of the sentence, e.g. at the level of words or even single frames. To do this we also plan to replace the “ad hoc” formula expressed by Equation \ref{eq:6} to weigh the KLD regularization term in Equation \ref{eq:4} by jointly optimizing both the DNN weights and the sentence-dependent regularization coefficients.

Based on the successful results obtained in the specific CHiME-3 application framework (read speech acquired by multiple microphones in noisy conditions), we also plan to extend our approach to other domains, possibly featuring higher degrees of acoustic mismatch for which the KLD-based regularization proposed in this paper seems to have the highest potential. Finally, an interesting direction to investigate is “incremental” DNN adaptation, where the DNN is periodically adapted on speech utterances and related transcriptions stored after they have been processed by the ASR system. This application scenario reflects the cross-condition experimental situation defined in Section \ref{sec:cross-condition} and, based on our current results, represents a promising and natural extension of this research.

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