

Investigating Cross-lingual Multi-level Adaptive Networks: The Importance of the Correlation of Source and Target Languages

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Outline

Motivation

Introduction

Multitask training and MLAN schemes

Experiments (setup & results)

Conclusions

Motivation

- General motivation
 - Exploiting data from other languages
 - For building robust models in under-resourced languages (or dialects)
 - data may be available, in a closely related (correlated) language

Correlation: phonetic similarity between the two languages.

- Our motivation
 - SUMMA H2020 project
 - Monitoring media/news in different languages
 - NLP topic clustering
 - Multilingual automatic speech recognition (ASR) in combination with machine translation for broadcast data monitoring
 - » Good resources: Arabic, English, German, Spanish
 - » Some resources: Portuguese, Russian, Farsi
 - » Poor resources: Ukrainian, Latvian

Introduction: Knowledge Transfer

- Exploiting out-of-domain (OOD) knowledge in ASR is not new!
 - in GMM/HMM frameworks (e.g. domain or speaker adaptation)
 - Maximum a posteriori (MAP) or
 - Maximum likelihood linear regression (MLLR)
 - in DNN/HMM frameworks
 - Adaptation by adding an extra input layer with a linear activation function (speaker adaptation)
 - Exploiting OOD data to better initialize the nets
 - Multi-task training
 - The output layer (i.e., softmax layer) could vary between domains during training
 - Sharing the hidden layers across domains
 - The tandem features
 - Concatenating bottleneck (BN) features derived from the OOD network with the in-domain acoustic features

Introduction: Cross-lingual ASR (1/2)

- Cross-lingual ASR is exploiting OOD knowledge
 - Target language models are enhanced using data from a different source language
 - The target language is low-resourced:
 - Transcribed data are difficult or expensive to be acquired
- Models are able to capture common properties of the acoustics of speech which are shared across languages, despite mismatches across languages.
 - Improving the generalization of the final models to unseen speakers and conditions
- Cross-lingual ASR techniques
 - Regularization
 - e.g. initializing nets on source data
 - Feature space
 - e.g. BN features
 - Hierarchical
 - e.g. combining nets into deep structure

Introduction: Cross-lingual ASR (2/2)

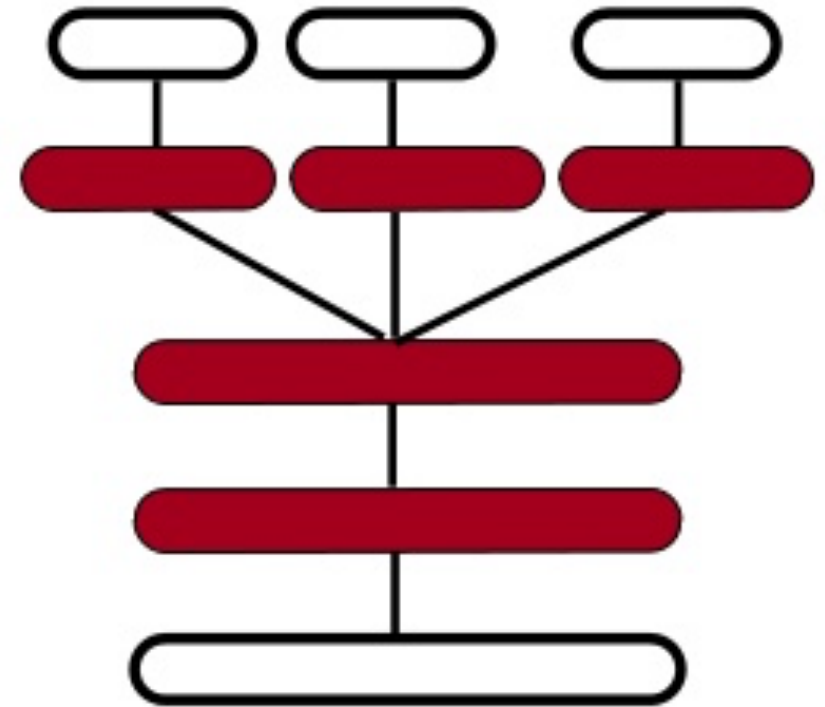
- Cross-lingual ASR is a form of adaptation
 - Major difference in respect to e.g. domain or speaker adaptation
 - Mismatch of the phonesets of source and target languages
 - Even with universal phonesets (IPA) the same phone, in practice, might differ across languages.
 - Mapping of phones manually or data-driven.
 - Separate phonesets could be used (i.e., different output layers in DNNs).

• We investigate the importance of the correlation of the source and target languages in the framework of cross-lingual adaptation.

• Multi-level adaptive networks (MLAN) scheme, aims to take advantage of BN features

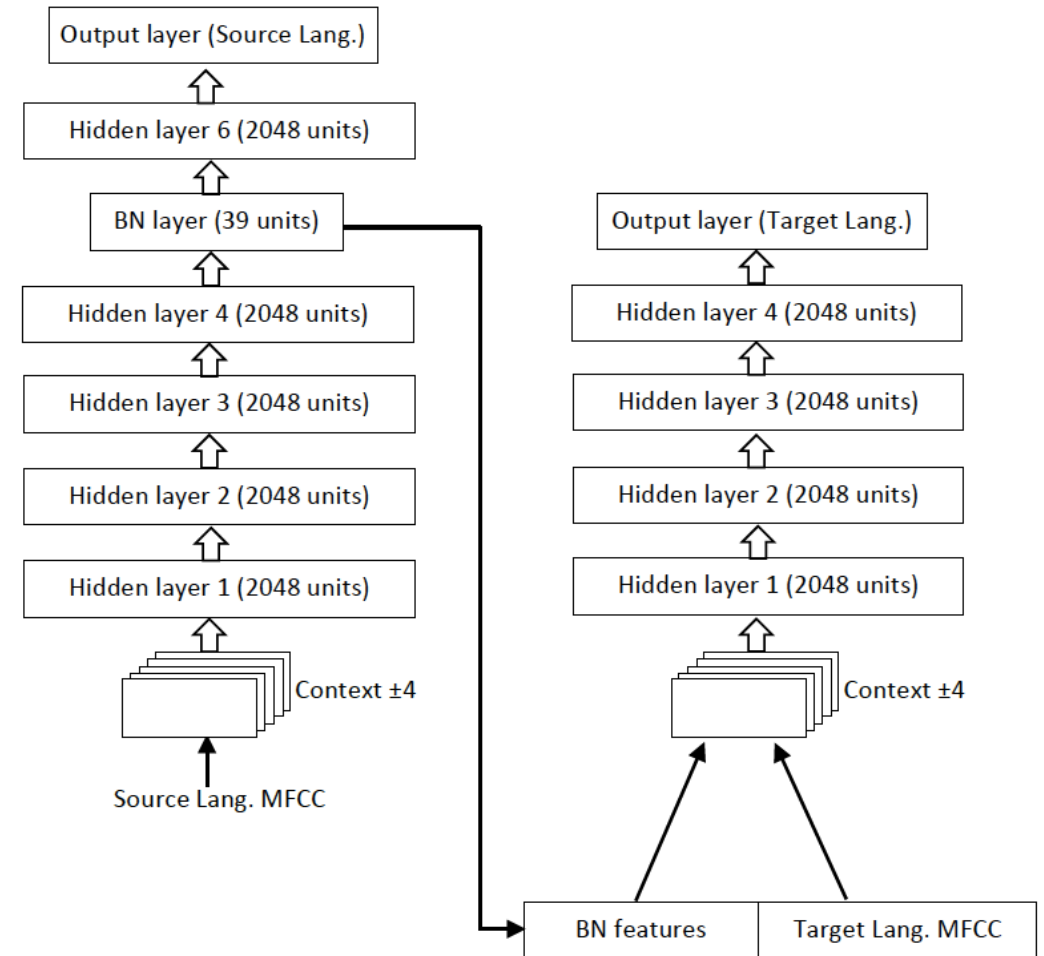
Multitask training

- The method of training a classifier to operate on two or more related tasks
 - A shared representation
 - Sharing lower hidden layers
 - Output layer (or even higher hidden layers) are task/language dependent
 - Multitask training increases the amount of data for each network
 - Aims to improve generalization of the model
 - The phoneset mismatch is dealt by swapping output layers during training



MLAN Scheme

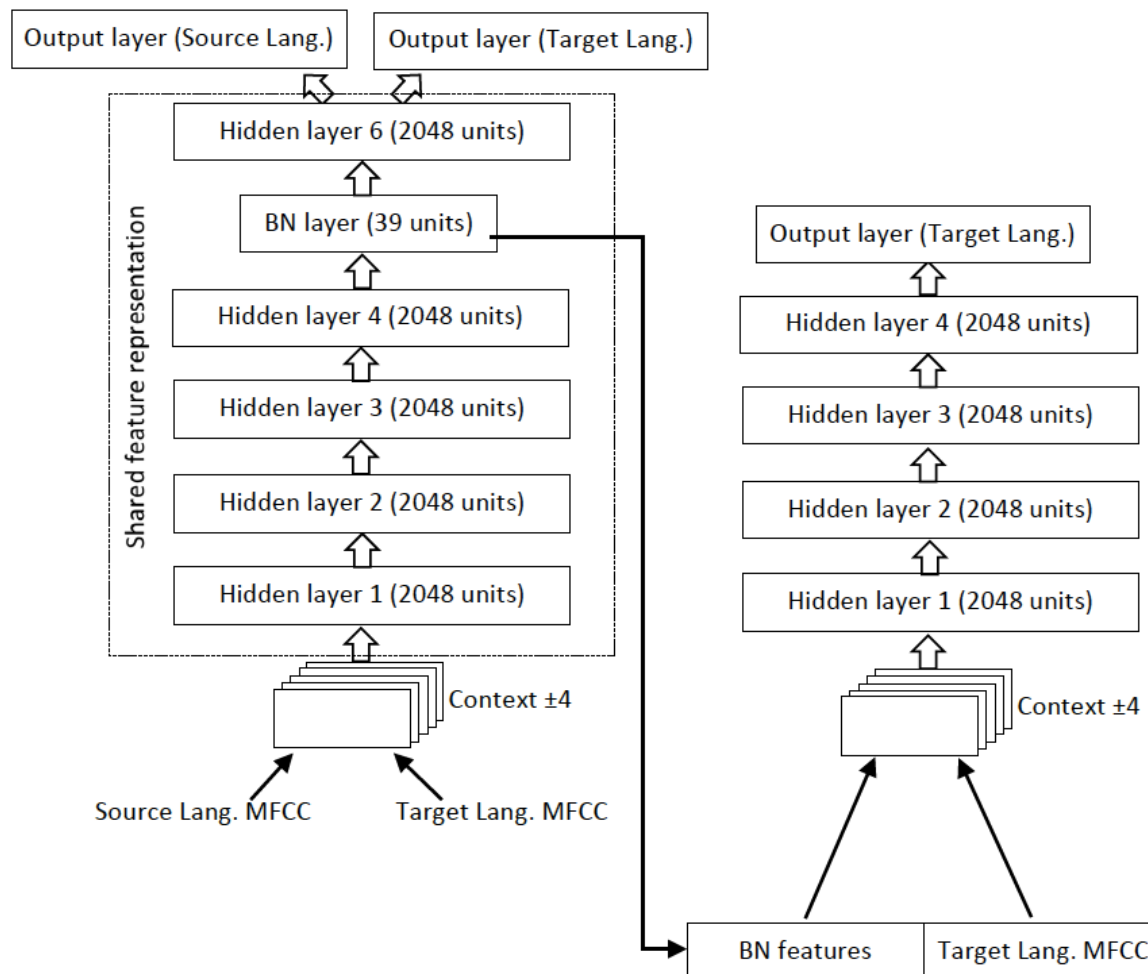
- Training a two-DNN structure
 - 1st DNN with BN layer is trained using OOD
 - Data from the source language
 - 2nd DNN trained with extracted BN features combined with in-domain (target language) spectral features



- The second-level DNN training is used to discriminatively select OOD features that are important for classification.

Multi-MLAN Scheme

- In multi-MLAN
 - Multi-task training for the 1st DNN
 - Source and target language tasks jointly
 - Using shared feature representation
 - The network effectively increases the amount of training data for each network.



- It allows a shared, language-independent speech representation to be learned.

Experimental Setup: Investigated Scenarios

- Russian used as target language (GLOBALPHONE)
 - Training set: 21 hours of speech,
 - split to 90% - 10% sets, training - cross-validation
 - Evaluation set: 1.6 hours (10 speakers)
- Source language scenarios
 - 1st: French, a language uncorrelated to the target one
 - a 47% overlap of phones in the phonesets
 - 25 hours of speech (GLOBALPHONE).
 - 2nd: Ukrainian, as correlated to the target one
 - a 79% overlap of phones in the phonesets
 - 11.5 hours of speech (GLOBALPHONE).
 - 3rd: French (size respective with the 2nd scenario)
 - 12.5 hours of speech (GLOBALPHONE).
 - 4th: English language (150 hours), as uncorrelated
 - a 45% overlap of phones in the phonesets
 - 50 hours from LIBRISPEECH
 - 50 hours from ICSIAMI
 - 50 hours from TEDLIUM

Experimental Setup: AM & LM

- Kaldi toolkit was used to build DNN/HMM system
- 39-dimensional MFCC features (including their delta and delta-delta)
- 9-frame temporal context
- 4 hidden layers of 2048 neurons/layer
- Sigmoid as activation function
- BN layer composed of 39 units.
- State alignments for training DNNs obtained from GMM/HMM system
- Dictionaries
 - CMU dictionary for English (39 phones)
 - GLOBALPHONE dictionaries
 - Ukrainian: 49 phones
 - French: 38 phones
 - Russian: 47 phones
- The decoding performed using a 3-gram LM developed based on GLOBALPHONE.

Results: General remarks

- All three cross-lingual adaptation schemes (in all scenarios) outperform the Baseline DNN
 - *Adaptation* case: Using source language net as initial net in target language
 - The *MLAN* improves the accuracy in respect to the *Adaptation*
 - The *multi-task MLAN* achieves the best performance

System	Source Language	WER(%)
Baseline	-	30.50
Adaptation MLAN	French (12.5h)	30.51
multi-task MLAN		28.86
Adaptation MLAN	French (25h)	28.20
multi-task MLAN		30.38
Adaptation MLAN	Ukrainian (11.5h)	28.66
multi-task MLAN		27.96
Adaptation MLAN	English (150h)	30.33
multi-task MLAN		28.56
Adaptation MLAN	English (150h)	28.00
multi-task MLAN		29.83
Adaptation MLAN	English (150h)	27.71
multi-task MLAN		27.62

Results: Importance of language correlation (1/2)

- In 1st&2nd scenarios, full French data and Ukrainian data, the performance is very similar.
 - The *Adaptation* outperform the Baseline DNN
 - by 0.4% relative improvement for French case.
 - by 0.6% relative improvement for Ukrainian case.
 - The *MLAN* outperforms the Baseline
 - by 6% relative improvement for French case.
 - by 6.4% relative improvement for Ukrainian case.
 - The *multi-task MLAN* outperforms the Baseline DNN
 - by 8.3% relative improvement for French case.
 - by 8.2% relative improvement for Ukrainian case.

System	Source Language	WER(%)
Baseline	-	30.50
Adaptation MLAN	French (12.5h)	30.51
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- We get similar results between correlated and uncorrelated source language cases, using double size of data for the uncorrelated source language.

Results: Importance of language correlation (2/2)

- 3rd scenario, using half of the French data
 - Matching approximately the amount of Ukrainian data
 - Accuracies of all three adaptation schemes were decreased in respect to the full French data case.
 - Using the correlated source language leads to slightly lower errors
- Validation of our hypothesis: Importance of the correlation of the source and target languages

System	Source Language	WER(%)
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Adaptation MLAN	French (12.5h)	30.51
multi-task MLAN		28.86
Adaptation MLAN	French (25h)	30.38
multi-task MLAN		28.66
Adaptation MLAN	Ukrainian (11.5h)	27.96
multi-task MLAN		30.33
Adaptation MLAN	Ukrainian (11.5h)	28.56
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Adaptation MLAN	English (150h)	27.62
multi-task MLAN		

Results: Importance of the amount of data

- 4th scenario, using English as source language, using 150 hours of data
 - Investigating the importance of the amount of training data used from the source language.
 - In all cases outperforms the scenario using the correlated source language
 - The highest improvement, over the Baseline system,
 - by 9.2% *MLAN* relative improvement.
 - by 9.4% *multi-task MLAN* relative improvement.

System	Source Language	WER(%)
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- Importance of using adequate amount of data from the source language.
- The difference between the two MLAN schemes is very small

Conclusions

- The MLAN and multi-task MLAN schemes were investigated
- French, Ukrainian and English as source languages,
- Russian as target language.
- Using French as the source language
 - the MLAN schemes needed to be trained with double the size of data of the ones used in the Ukrainian case
- Using less French data (half size),
 - the performance was decreased in respect to the scenario where the Ukrainian data were used.

- The results showed the importance of the correlation between the source and target languages.

- Using English as source language (6 times and 13 times more training data)
 - the MLAN and multi-task MLAN schemes achieved the highest relative improvement

- The results have shown the importance of the amount of source language data used.
- It is worth training using large amounts of uncorrelated data.

Thank you!

Questions?