Merging of native and non-native speech for low-resource accented ASR

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Outline

Introduction

- Performance of non-native automatic speech recognition (ASR) is poor when few (or no) non-native speech is available for training / adaptation.
- Many approaches have been suggested for handling accented-speech in ASR:
  - acoustic model merging ((Morgan, 2004), (Bouselmi, Fohr, and Haton, 2005), (Tan and Besacier, 2007), (Tan, Besacier, and Lecouteux, 2014)),
  - applying maximum likelihood linear regression (MLLR) for adapting models to each non-native speaker (Huang et al., 2000), or
  - adapting lexicon ((Arslan and Hansen, 1996), (Goronzy, 2002))

Introduction contd.

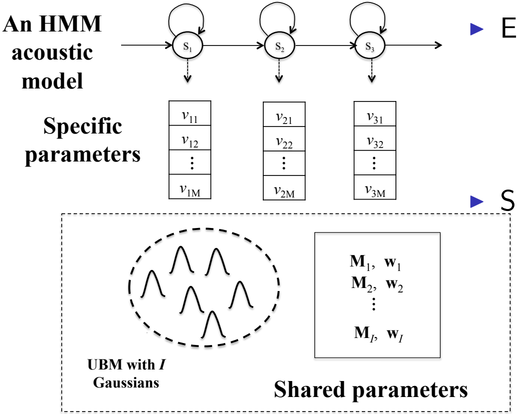
- Multi-accent approach for accented speech:
  - Subspace Gaussian Mixture Model (Mohan, Ghalehjegh, and Rose, 2012) and Deep Neural Network (Huang et al., 2014) - apply pooling data approach
- **Can we finely merge unbalanced corpora (large native data $<->$ small non-native data) for achieving an optimal acoustic model?**

Outline

Subspace Gaussian Mixture Model

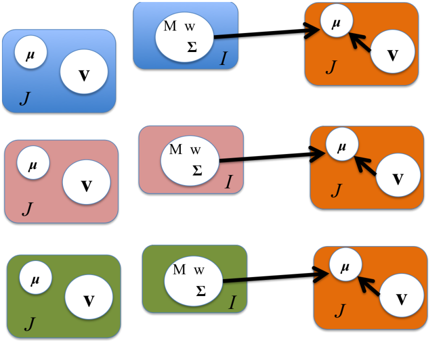
General

Subspace Gaussian Mixture Model (SGMM) (Povey et al., 2010):



- Each HMM state:
  - Defined by a low-dimensional vector v_{jm}
  - Mixture of substates
- Shared parameters:
  - Universal Background Model (UBM)
  - Means, $\mathbf{M}_i$
  - Mixture weights, $\mathbf{w}_i$

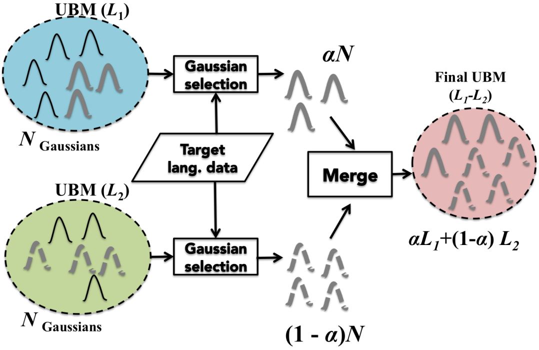
Multi-accent SGMM



Using SGMM:

- Transfer shared parameters from source to target system
- Applied by (Imseng et al., 2014) and (Lu, Ghoshal, and Renals, 2014) - cross-lingual acoustic model for low-resource systems

Language-weighting strategy for multi-accent SGMM

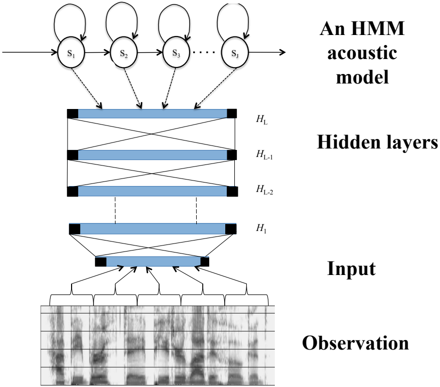


- UBM Gaussians, e.g. $N = 500$
- L_1 = Non-native
  L_2 = Native
- Weights, α= 0.1, 0.2, ..., 0.9.

Deep Neural Networks

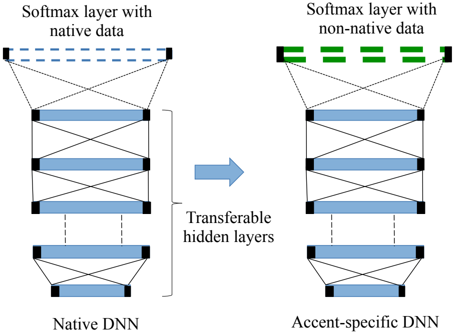
General

Deep Neural Networks (DNN) (Hinton et al., 2012):



- Alternative to HMM/GMM systems
- Feedforward neural network
- Intialization of DNN weights:
  - Random
  - Pretraining - Restrictive Boltzmann Machines (RBM) (Hinton, 2010)
- Adjust weights - Stochastic Gradient Descent

Accent-specific top layer DNN



1. Train DNN on Native / Non-native data:
2. Remove last layer (softmax layer) from DNN with native speech
3. Fine-tune hidden layers on non-native training data

Outline

Experimental setup

- Non-native - Malaysian English (Tan, Besacier, and Lecouteux, 2014):
  - Train: 2h transcribed; 9h untranscribed (UBM - 11h)
  - Test: 4h
- "Native" - TED English[1] (TED-LIUM) (Rousseau, Deléglise, and Estève, 2012)
  - Train: 118h
  - Test: 4h
- Toolkit: Kaldi
- Systems:
  - HMM/GMM
  - HMM/SGMM :
    - UBM 500
    - Merging: $\alpha = 0.1, ..., 0.9$
    - substates 800 to 8750
  - HMM/DNN : 6 hidden layers with 1024 units

[1] Even if non-native speakers exist in the corpus

Outline

Introduction

Acoustic Model Merging Approach

Experimental Setup

Performance of Non-native ASR

Conclusions

Baseline results (WER %)

English ASR results for native and non-native speech
- no speaker adaptation (fMLLR) at this stage

Train	Test	
	Native (4h)	Non-native (4h)
Native 118h	30.55 (GMM) 28.05 (SGMM) **19.10 (DNN)**	
Non-native 2h		

Baseline results (WER %)

English ASR results for native and non-native speech
- no speaker adaptation (fMLLR) at this stage

Train	Test	
	Native (4h)	Non-native (4h)
Native 118h	30.55 (GMM) 28.05 (SGMM) **19.10 (DNN)**	57.09 (GMM) 45.84 (SGMM) **40.70 (DNN)**
Non-native 2h		

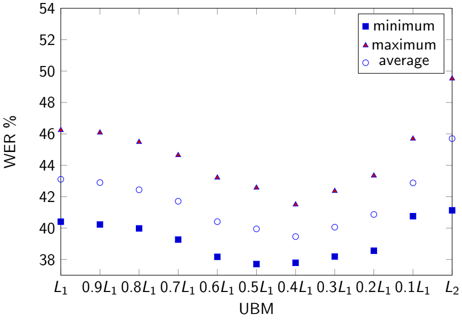
Baseline results (WER %)

English ASR results for native and non-native speech
- no speaker adaptation (fMLLR) at this stage

Train	Test	
	Native (4h)	Non-native (4h)
Native 118h	30.55 (GMM) 28.05 (SGMM) **19.10 (DNN)**	57.09 (GMM) 45.84 (SGMM) **40.70 (DNN)**
Non-native 2h		41.47 (GMM) 40.41 (SGMM) **32.52 (DNN)**

Multi-accent SGMM results

L_1: Malaysian English, L_2: TED English



- 4h test data
- **Best WER: 37.7%** - Baseline: 40.4%
- $\alpha = 0.5$ (250 Gaussians from L_1/L_2)
- Increase substates degrades results

Accent-specific top layer for DNN

DNN with accent-specific top layer	WER (%)
Baseline - standard DNN	32.52
No speaker adaptation	24.89
Speaker adaptation	21.48

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Conclusions

- Proposed two approaches for optimal merging of native and non-native data in order to improve accented ASR with limited training data:
  1. Language weighting strategy for multi-accent compact SGMM acoustic models - used language weights to control the number of UBM Gaussians.
  2. Fine-tuning hidden layers of native DNN on the non-native training data
- Observed improvements on non-native ASR performance:
  - Relative improvement: 15% for SGMM (multi-accent UBM500 - $\alpha = 0.5$) and 34% for DNN (accent-specific with speaker adaptation).


thank you
danke
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gracias
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спасибо
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Баярлалаа
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mochchakkeram
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terima kasih
감사합니다
ありがとう
arigatô
dakujem
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