

# Multi-Feature Modular Deep Neural Network Acoustic Models

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## Overview



#### Introduction

- Feature combination in neural networks
  - Used features
  - Combination approaches
- Modular deep neural network acoustic models
  - Motivation
  - Topology
  - Multiple modules
- Results

# Introduction



- Goal: Combination of multiple input features
- Approach: Modular Deep Neural Network Acoustic Models
- Evaluated on the following German test sets
  - IWSLT dev2012:
    - TED and TEDx talks
    - 2 hours of audio from 7 speakers with a total of 18k words
    - Word error rate measured using 3 significant figures
  - Quaero eval2010:
    - Podcasts, talkshows, broadcast news
    - 3.5 hours of audio from 135 speakers with a total of 32k words
    - Word error rate measured using 4 significant figures
- Baseline system: KIT 2014 IWSLT system

### Feature combination in neural networks



- Many approaches
  - Disregard irrelevant information: speaker, background noise, ...
  - Fundamentally similar and often equally useful
- Can be complementary
- ASR systems using different features can be combined for better results
- Neural networks can be used to combine multiple features in a single ASR system
  - C. Plahl, R. Schlüter, and H. Ney, "Improved acoustic feature combination for lvcsr by neural networks.", INTERSPEECH, 2011
  - K. Kilgour, T. Seytzer, Q. Nguyen, and A. Waibel, "Warped minimum variance distortionless response based bottle-neck features for LVCSR," ICASSP, 2013
  - C. Plahl, M. Kozielski, R. Schlüter, and H. Ney, "Feature combination and stacking of recurrent and non-recurrent neural networks for lvcsr," ICASSP, 2013
  - F. Metze, Z. A. Sheikh, A. Waibel, J. Gehring, K. Kilgour, Q. B. Nguyen, and V. H. Nguyen, "Models of tone for tonal and non-tonal languages," ASRU, 2013

### Features



#### MFCC

- 20 dimensional feature vector
- Standard ASR feature for the past two decades
- MVDR
  - 20 dimensional feature vector
  - Improves on linear prediction features
  - M. Wölfel, J. W. McDonough, and A. Waibel, "Minimum variance distortionless response on a warped frequency scale." INTERSPEECH, 2003

#### IMEL:

- 40 dimensional feature vector
- Precursor feature to MFCC features
- Typically outperform MFCCs in large DNNs
- Tonal:
  - 14 dimensional feature vector
  - Combination of pitch (7) & FFV (7) feature vectors
  - Can not be used as stand alone features
  - F. Metze, Z. A. Sheikh, A. Waibel, J. Gehring, K. Kilgour, Q. B. Nguyen, and V. H. Nguyen, "Models of tone for tonal and non-tonal languages," ASRU, 2013

### Neural Network Feature Combination Approaches 🛓

- Deep bottle neck features
- Deep neural network acoustic models





softmax output layer: CD - phone state

# Multi-Feature DBNF





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# Multi-Feature DBNF Results





- Significant improvements on both test sets:
  - dev2012: 0.8% (vs. baseline)
    & 0.5% (vs. best single feature)
  - eval2010: 1.23% (vs. baseline)
    & 0.5% (vs. best single feature)



### Multi-Feature DNN AM





















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## Modular DNN AM Results



	eval2010	dev2012
MFCC	15.35	19.5
+MVDR	14.71	19.4
+Tone	14.54	19.3
+IMEL	14.31	18.9
IMEL	14.72	19.5
+Tone	14.52	19.0
MVDR	14.81	19.5

# mDNN AM with Multiple BNF Modules







	BNF modules	eval2010	dev2012
IMEL+Tone	1	14.52	19.0
MFCC+MVDR+Tone	1	14.54	19.3
MFCC+MVDR+Tone+IMEL	1	14.31	18.9
MFCC	1	15.35	19.5
$\oplus$ MVDR	2	14.54	19.2
⊕ IMel	3	14.73	19.3
$MFCC  \oplus  MVDR  \oplus  IMel+Tone$	3	14.24	18.7
$IMEL+Tone \oplus MFCC+MVDR+Tone$	2	14.19	18.8
$\oplus$ MFCC+MVDR+Tone+IMEL	3	14.06	18.7
$\oplus$ MFCC $\oplus$ MVDR	5	14.33	18.9
$\oplus$ IMEL $\oplus$ MFCC+MVDR	7	14.44	18.8
$IMEL \oplus MFCC + MVDR$	2	14.34	19.1

# **Results Summary**



	eval2010	dev2012
baseline MFCC DNN	15.88	20.3
best single-feature DNN	15.31	20.1
best DNN system combination (CNC)	14.45	19.2
best multi-feature DNN	14.71	19.4
best mDNN with a single module	14.31	18.9
best mDNN with multiple modules	14.06	18.7

# Conclusion



- DNNs can benefit from multiple input features
- A modular DNN topology can improve its quality
- Multiple feature modules can outperform networks with only a single module
- simply concatenating all features in the input layer is no longer the best approach