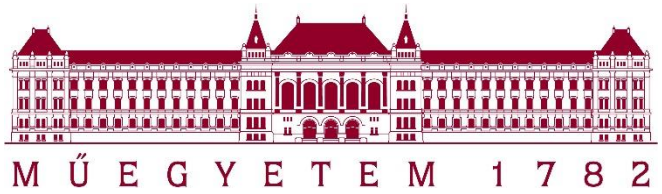

Continuous Fundamental Frequency Prediction with Deep Neural Networks

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Introduction

Deep Learning: New era of machine learning

Feed forward deep neural networks

Speech research

- Speech recognition
- Speech coding
- Speech synthesis: using parametric vocoders
  - spectral components,
  - phone durations,
  - fundamental frequency (= pitch = F0).

Fundamental frequency prediction

Rule based F0 prediction

Statistical / machine learning approach

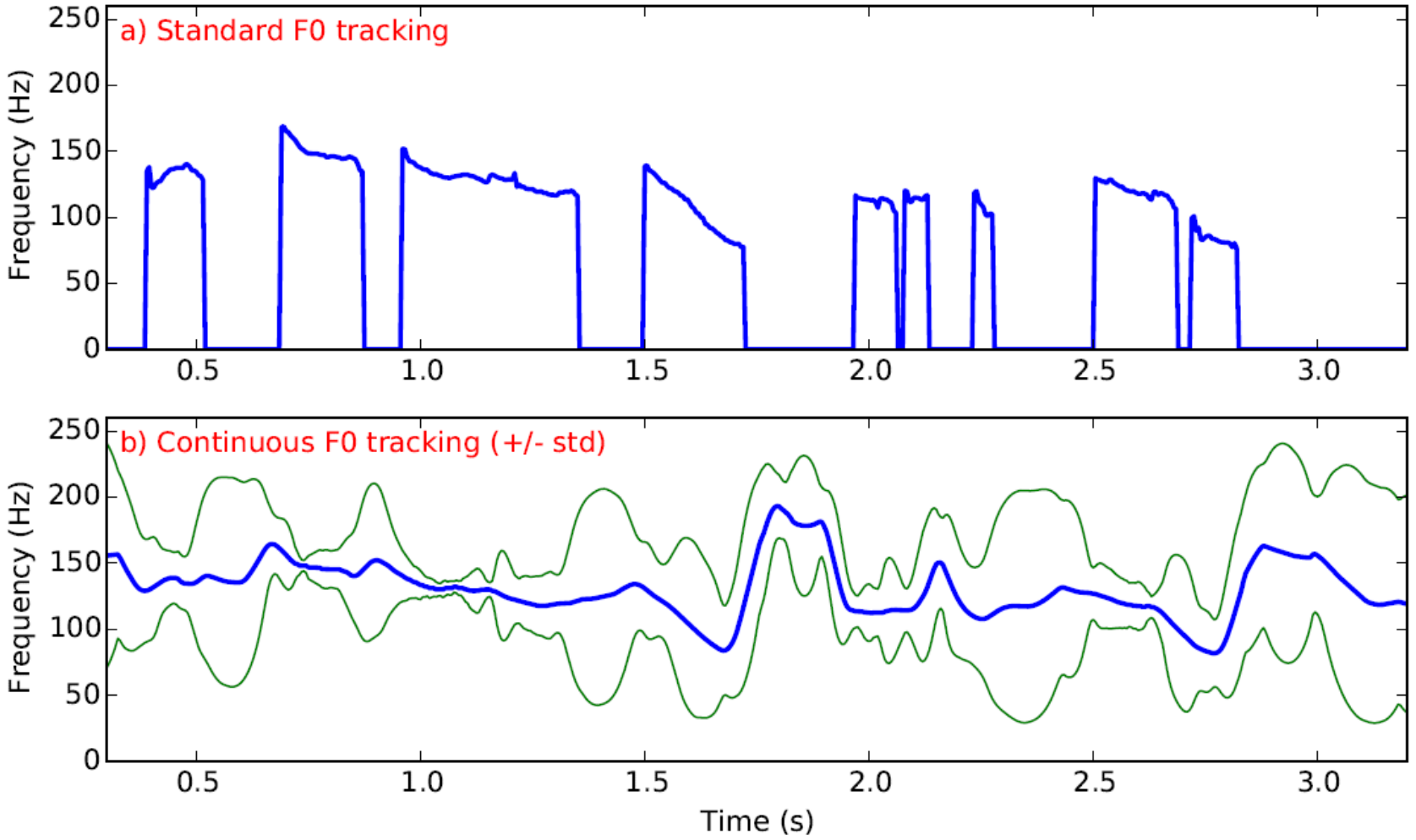
- Hidden Markov Models (HMM)
- Feed forward deep neural networks (DNN)

Pitch tracking algorithm

- Vanilla: Standard F0 tracking + voiced/unvoiced tagging
  - Difficulty in modeling standard F0
  - Discontinuity in unvoiced regions
  - Multi-Space Distribution Hidden Markov Models (MSD-HMM)

- Proposed: Continuous F0 + Maximum Voiced Frequency
  - No discontinuity, less difficulty in modeling

Continuous Pitch Tracking



'I saw it all myself, and it was splendid.'

Goal

Investigation of

1) feed forward deep neural networks modeling power,
2) model complexity of vanilla and continuous F0 trajectories

Hypothesis

Perceptual quality of DNN-based prediction using continuous F0 will be superior to discontinuous F0

Vocoder methods I: Standard F0 (baseline)

Pulse-noise vocoder

SWIPE pitch tracking algorithm (Camacho & Harris 2008)

2 parameters for every 25 ms long (5 ms shift) window:

- F0 value for voiced regions
  - For DNN, linear interpolation in unvoiced regions
- Voiced / unvoiced binary flag

Denoted by F0std

Vocoder methods II: Continuous F0

Residual-based continuous vocoder

SSP pitch tracking algorithm (Garner et al., 2013)

2 parameters for every 25 ms long (5 ms shift) window:

- F0 value for all regions
- Maximum Voiced Frequency (MVF)
  - Voiced-unvoiced frequency boundary

Denoted by F0cont

Machine Learning Methods: HMM

Widespread statistical parametric
speech synthesis approach

Vocoder I

- F0std training and prediction (with MSD-HMM)

Vocoder II

- F0cont & MVF training and prediction

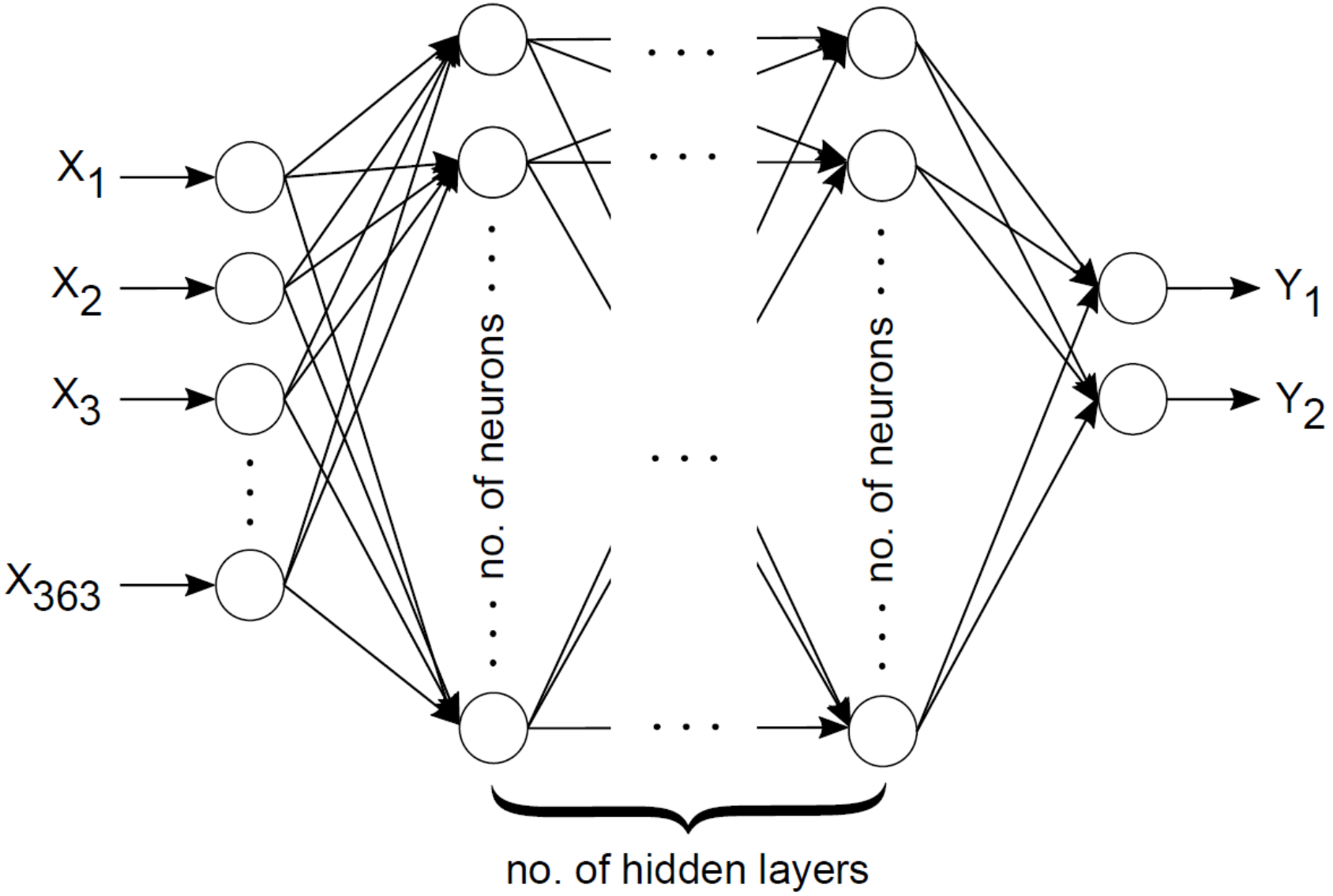
HTS 2.3 with default settings

Machine Learning Methods: DNN

Feed forward deep neural networks

- Mean Square Error (MSE) cost function
- ADADELTA optimization with mini-batches
- Parametric Rectified Linear Units (PReLU) as activation function for hidden layers
- Sigmoid activation function for the outputs
- Weight initialization:
  - Xavier's weight input-hidden and hidden-output layers
  - Orthogonal in the hidden layers
- Dropout w/ 50% after each layer except output layer
- Early stopping after 50 epochs

Proposed DNN network



DNN Inputs

Parameter-wise transformed
to zero mean and unit variance

Feature name	#	Type
Quinphone	5*68	One-hot
Number of phonemes/syllables/words/phrases in the previous/current/next syllable/word/phrase/sentence	4*3	Numerical
Number of syllables/words in the current sentence	2	Numerical
Forward/backward position of the actual phoneme/syllable/ word/phrase in the syllable/word/phrase/sentence	2*3	Numerical
Phone boundaries	2	Numerical
Percentual position of the actual frame within the phone	1	Numerical
Altogether:	**363**	

DNN Outputs

Normalized to 0.01…0.99 for sigmoid activation

System	Feature name	#	Type
F0std	LogF0	1	Continuous (interpolated)
	V/UV flag	1	Binary
F0cont	LogF0	1	Continuous
	MVF	1	Continuous

Evaluation: hyperparameter optimization

One male and one female speaker from Precisely Labelled Hungarian Database (PLHD)

1984 utterances / speaker (~2 hours)

Training-validation-test sets: 80-15-5%

Hyperparameter optimization with male speaker:

- #hidden layers: 1..7
- #neurons / layer: 80..2048
- #mini-batch size: 8..256

Validation loss was measured.

64 neural nets for F0std and 73 for F0cont

Top 5 were selected and run with female speaker

Hyperopt results: standard F0

ID	# Hidden Layers	# Neurons	Epochs	Validation MSE
F0std-1	3	350	61	0.01076
F0std-2	3	650	32	0.01078
F0std-3	3	900	30	0.01089
F0std-4	3	950	36	0.01099
F0std-5	3	800	37	0.01103

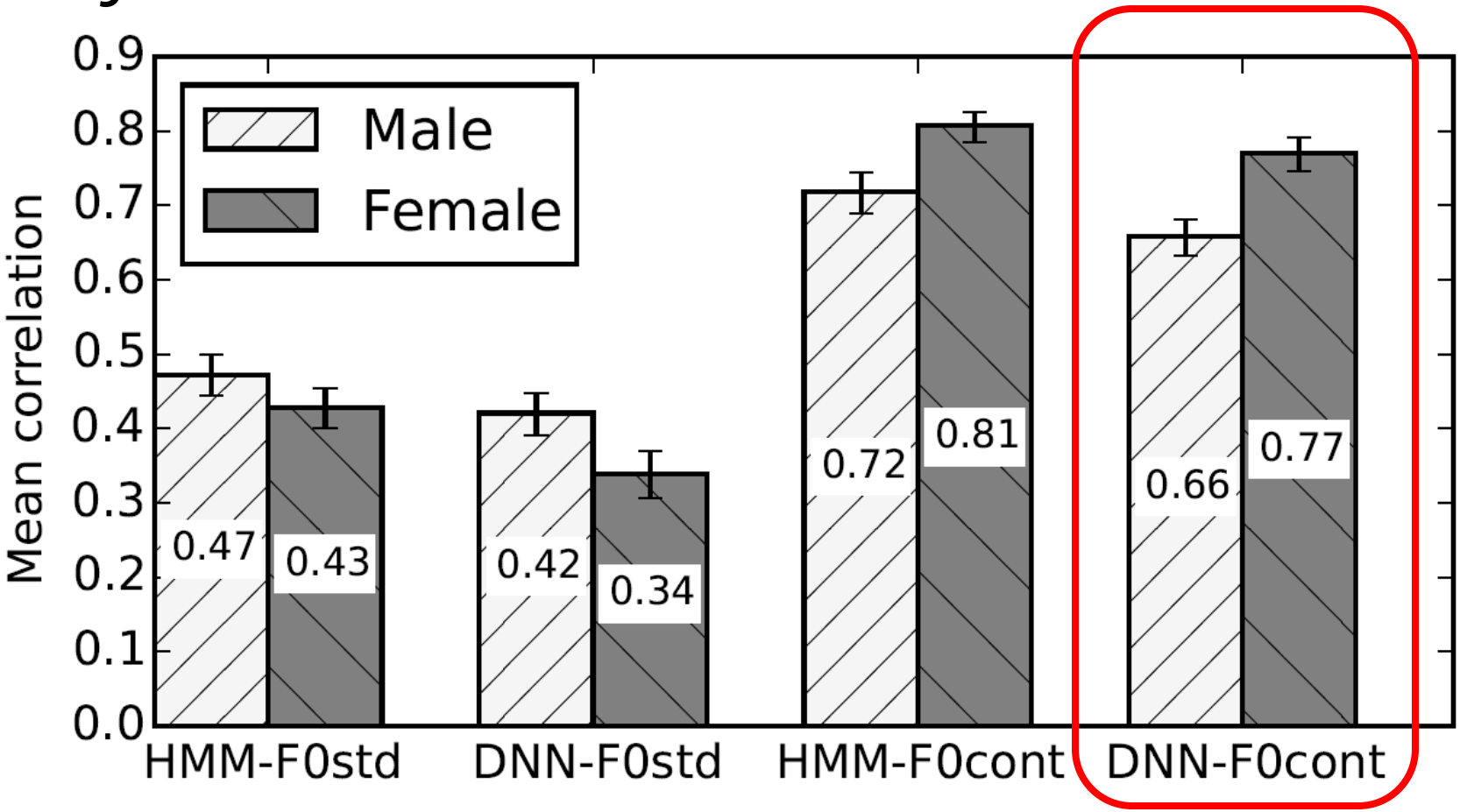
Mini-batch size = 128

Hyperopt results: continuous F0

ID	# Hidden Layers	# Neurons	Epochs	Validation MSE
F0cont-1	3	160	2	0.00239
F0cont-2	3	80	67	0.00346
F0cont-3	1	128	2	0.00349
F0cont-4	3	70	12	0.00352
F0cont-5	2	100	28	0.00356

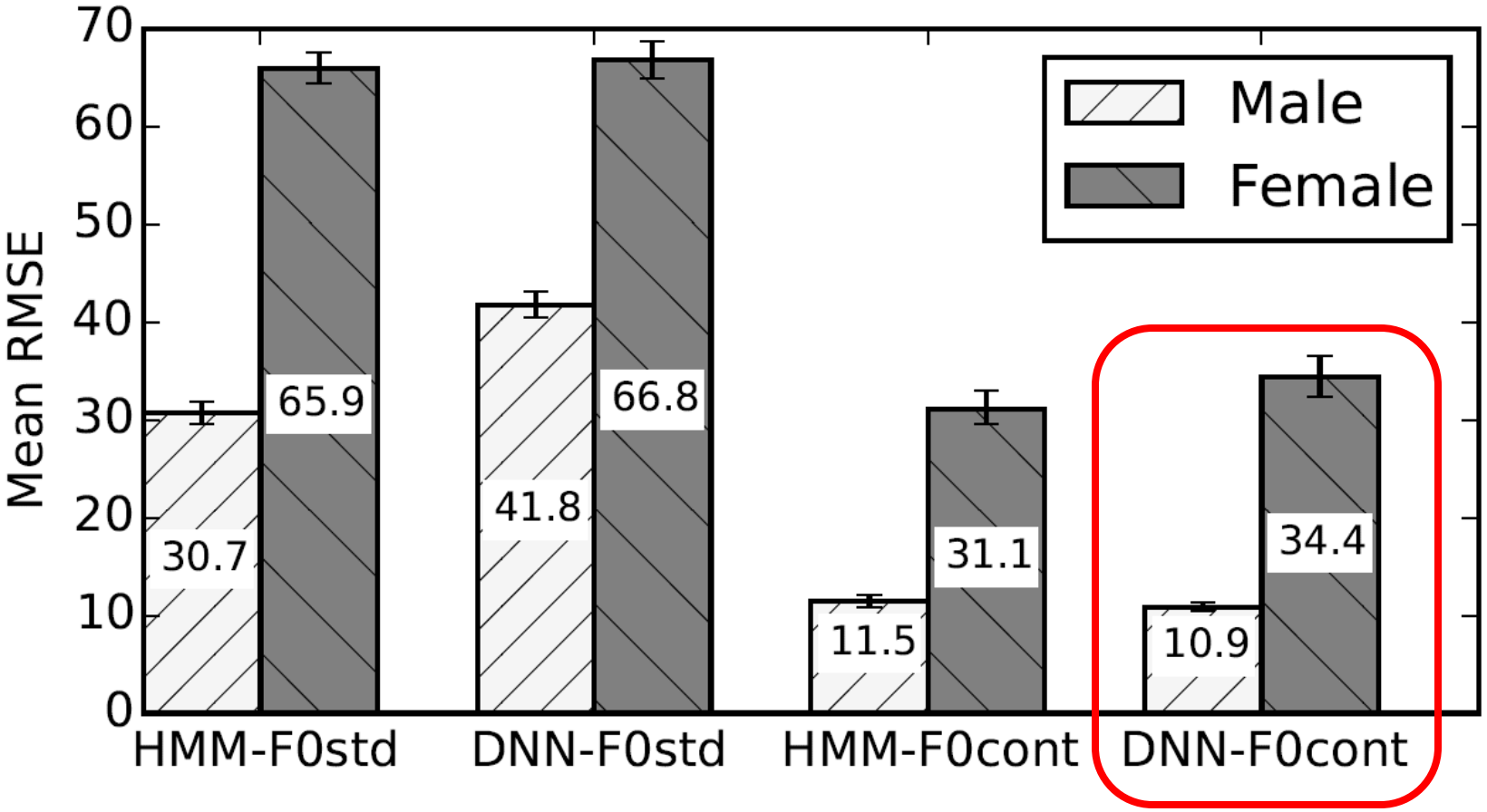
Mini-batch size = 8

Objective evaluation I



Mean correlation between natural F0 and modeled F0 (higher value: larger similarity between compared F0 trajectories)

Objective evaluation II



Mean RMSE between natural F0 and modeled F0 (higher value: larger difference between compared F0 trajectories)

Subjective evaluation I

Goal: measure the perceived intonation of sentences

Web-based MUSHRA test:

- Reference natural sentence,
- Vocoded sentence with F0 from
  - Natural utterance
    - F0std
    - F0cont
  - HMM
    - F0std
    - F0cont
  - DNN
    - F0std
    - F0cont
- Benchmark: vocoded with F0=0

Subjective evaluation II

Sentences with highest RMSE were selected

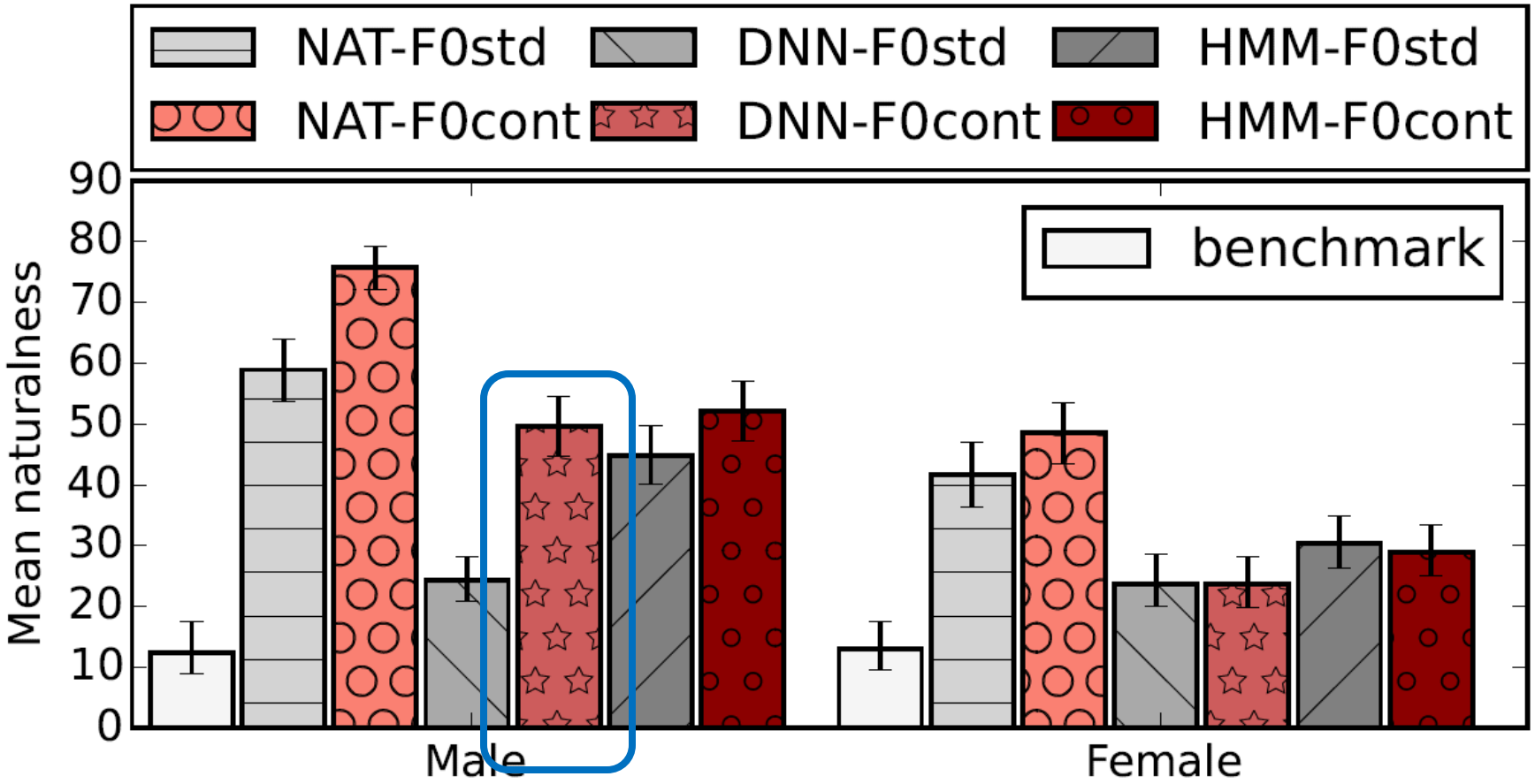
2 speakers × 8 types × 5 sentences (altogether 80 sent.)

Randomized order

18 test subjects (9 females, 9 males)

13 minutes to complete the test (avg)

Subjective evaluation III

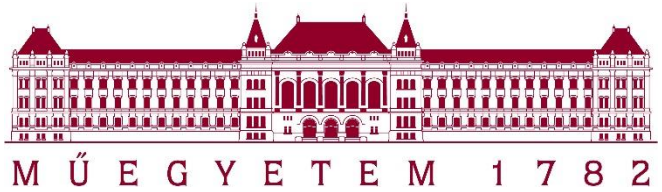


(higher value: more similar to natural)

Conclusions and discussion

1) F0cont can be predicted better than F0std with HMMs and DNNs
2) Simpler DNN models for F0cont (good for embedded systems)
3) F0cont has faster convergence (we measured cca. 7x faster than F0std)
4) Simple DNN approaches the F0 modeling capacity of state-of-the-art HMM

→ continuous representation of F0 forms a less complex system than the V/UV based F0std



Thanks for listening!

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