# ADAPTING AND CONTROLLING DNN-BASED SPEECH SYNTHESIS USING INPUT CODES

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# Background

## Statistical parametric speech synthesis

- Remarkable progress thanks to DNN
- e.g. Wavenet, SampleRNN, GAN

## Flexibility of speech synthesizers

- HMM-based synthesis
  - Speaker/style adaptation, interpolation, multiple regression
- DNN-based synthesis
  - Black-box, not as flexible as HMM synthesizers yet

## Speaker, gender, and age codes: “**input codes**”

- Multi-speaker modelling
- Speaker adaptation

Objective and subjective results

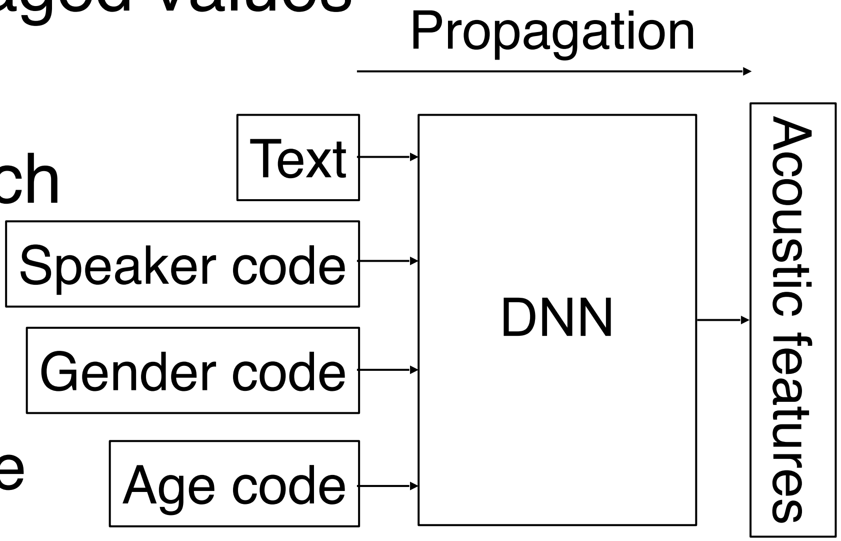
- Flexible manipulation

Demonstration

# Multi-speaker modelling using input codes

## Multi-speaker modelling using input codes

- Generate multiple speakers' voices from a single DNN
- Input codes: simple additional inputs that differentiate ID, gender and age of speakers
- Also good as an initial model for speaker adaptation
  - Input codes that use averaged values
    → Average voice
- Allow us to manipulate speech
  - e.g. flip the gender code
- Morphing
  - Change the code each frame



# Speaker codes

## One-hot vector codes

$\boldsymbol{s}_i = (s_1,\ s_2,\ ...,\ s_N)$ $s_i$ : $1$ other: $0$

$N$ : # speakers $i$ : index

Simple, Widely used

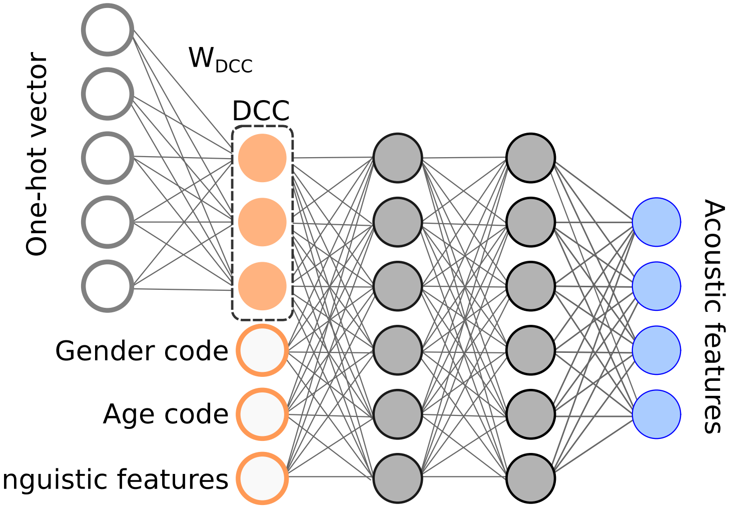
## Random-vector codes

$\boldsymbol{s}_i = (s_1,\ s_2,\ ...,\ s_K)$ $s_k$ : unique and random value

$K$ : Dimension

Easy to change the dimension

## Discriminant condition codes



– Projection of one-hot vector
– Project matrix: W_dcc
– Codes trained jointly with other parameters

Data-driven

# Gender and age codes

## One-hot vector

- – Gender: 2 dimensions (1st dim: female, 2nd dim: male)
- – Age: 7 dimensions (10’s, 20’s, …, 70’s)

## Binary/numerical representation (1 dimension)

- – Gender: binary (0: female, 1:male)
- – Age: use the age directly
- – Probably more intuitive easy-to-control representation

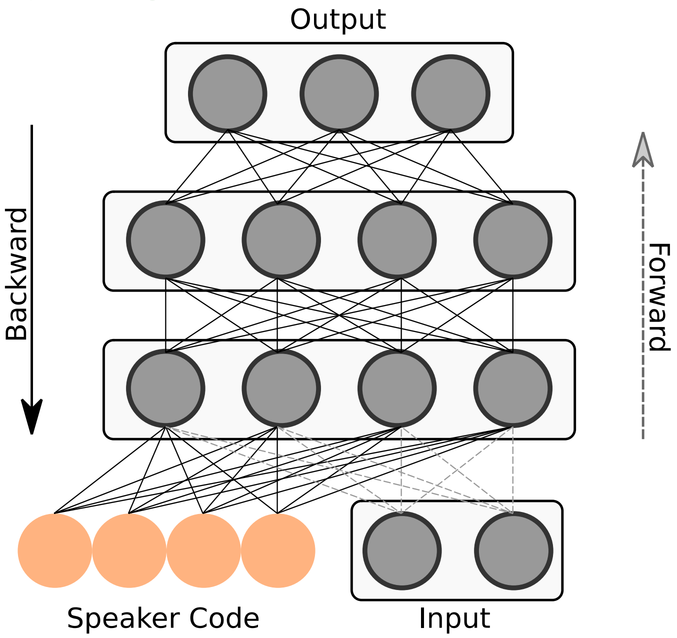
# Adaptation using input code: ‘***phantom code***’

## Estimate speaker code using adaptation data

- Estimation based on back-propagation [Bridle et al.; 90]
- Estimate the speaker code only, fix the other codes and other DNN parameters

## Update procedures of the speaker codes

- Initialize the codes with the average
- Update the codes
  - Fixed maximum number of epoch:
  - Fixed learning rate
- Choose codes that has minimum errors
- Simple!!
-



# Experimental conditions

| Multi-speaker | | | | Adaptation | | | |
|---|---|---|---|---|---|---|---|
| Age | Male | Female | Total | Age | Male | Female | Total |
| 10-20 | 8 | 8 | 16 | 10-20 | 0 | 2 | 2 |
| 21-30 | 8 | 8 | 16 | 21-30 | 2 | 2 | 4 |
| 31-40 | 8 | 8 | 16 | 31-40 | 2 | 2 | 4 |
| 41-50 | 8 | 8 | 16 | 41-50 | 1 | 2 | 3 |
| 51-60 | 8 | 8 | 16 | 51-60 | 2 | 2 | 4 |
| 61-70 | 8 | 8 | 16 | 61-70 | 2 | 2 | 4 |
| 71- | 8 | 8 | 16 | 71- | 0 | 2 | 2 |
| Total | 56 | 56 | **112** | Total | 9 | 14 | **23** |

– High-quality Japanese speech database

– Training: 112 speakers, 100 utterances per speaker, total of 11,170 utterances

– Adaptation: 23 speakers, 100 utterances per speaker

– Test: 10 different sentences per speaker

# Experimental conditions (contd.)

## Acoustic features (outputs)

- 60-dim STRAIGHT mel-cepstrum$+\Delta + \Delta^2$
- Voiced/unvoiced flag
- Log F0 $+\Delta + \Delta^2$
- 25-dim band-limited aperiodicities $+\Delta + \Delta^2$

## Text features (inputs)

- Open JTalk: 386-dim linguistic features
- Phone duration
  - Use oracle duration to compute objective measures
  - HMM-based forced-alignment
- Input codes

# Experimental conditions (contd.)

| | Speaker code<br>（S） | | Gender code<br>（G） | | Age code （A） | |
|---|---|---|---|---|---|---|
| Model label | Type | Size | Type | Size | Type | Size |
| ONE-S | One-hot | 112 | N/A | N/A | N/A | N/A |
| ONE-SGA’ | One-hot | 112 | One-hot | 2 | One-hot | 7 |
| ONE-SGA | One-hot | 112 | Binary | 1 | Numeric | 1 |
| RND112-SGA | Random | 112 | Binary | 1 | Numeric | 1 |
| RND008-SGA | Random | 8 | Binary | 1 | Numeric | 1 |
| DCC112-SGA | DCC | 112 | Binary | 1 | Numeric | 1 |
| DCC008-SGA | DCC | 8 | Binary | 1 | Numeric | 1 |

– Simple feed forward DNN

– Hidden layers: 5, units: 1024

– Activation function: sigmoid

– Learning rate: 0.05, 10 epochs

– Objective measures: Mel-cepstral distortion, F0 RMSE

# Objective evaluation: Multi-speaker modelling

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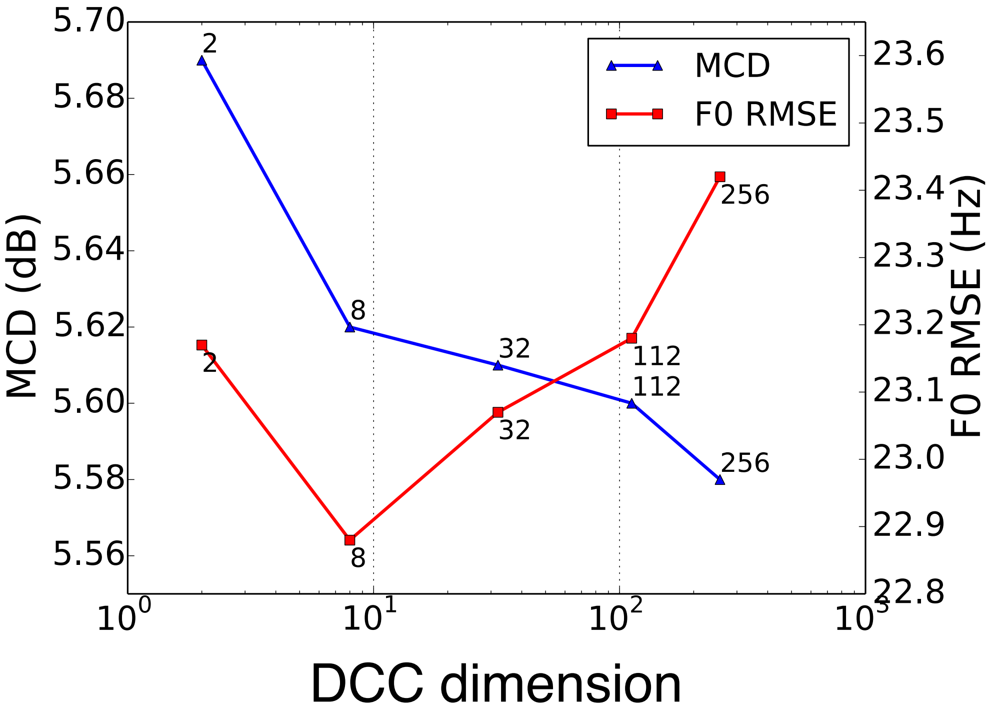

- Evaluation using training speakers' codes
- ONE-c: correct code
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  - Possible to model multiple speakers simultaneously
- No significant differences between code representations
- Preferable DCC dimension depends on acoustic features

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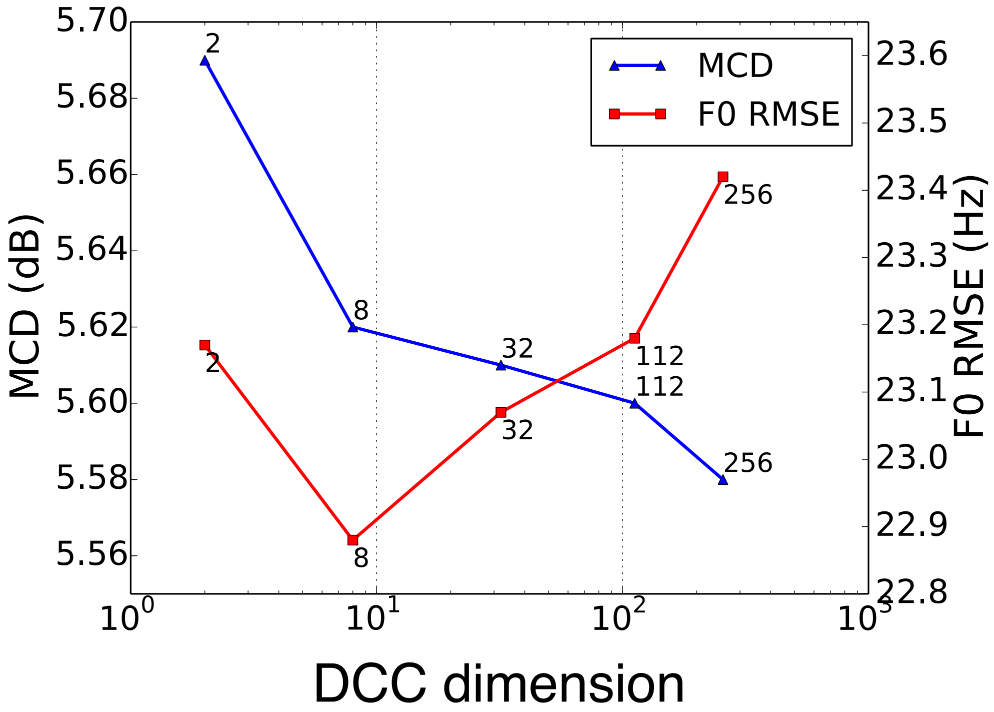

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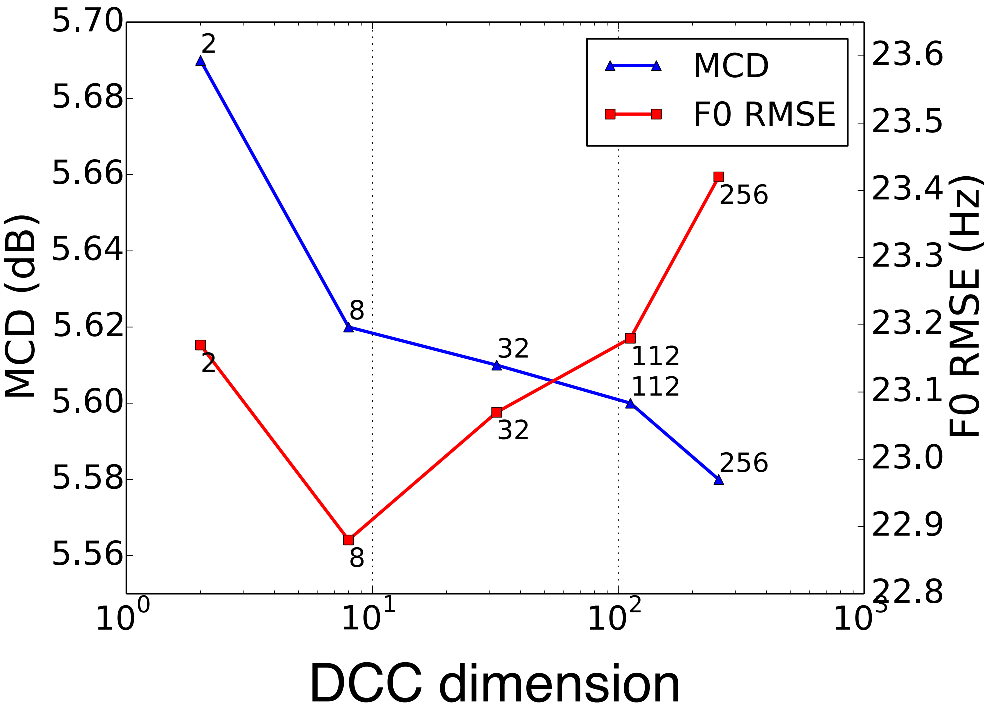

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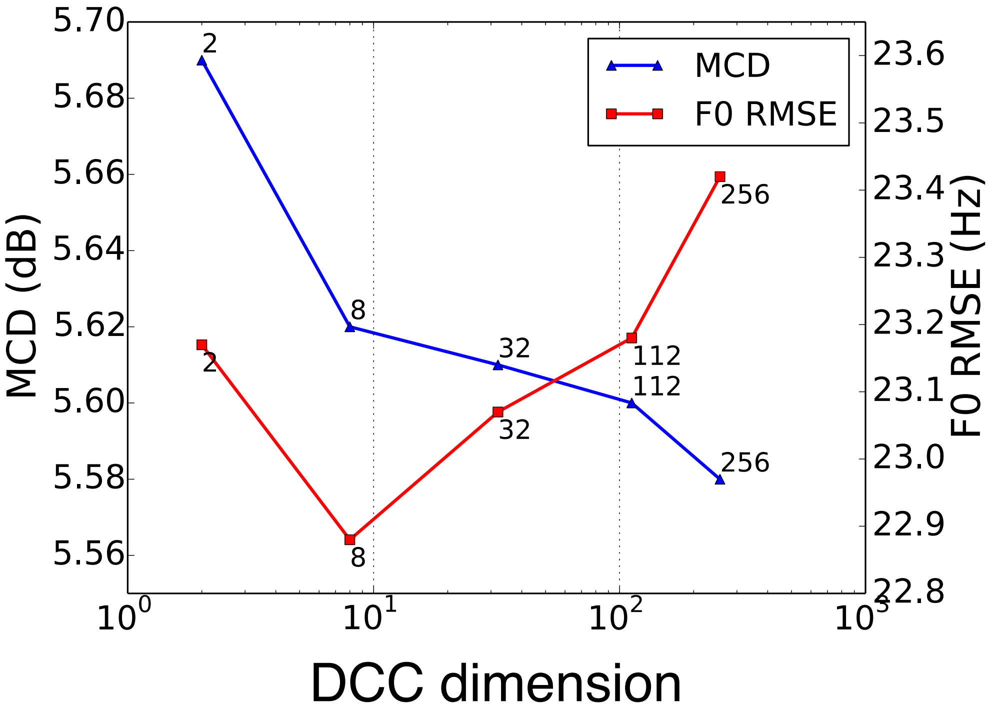

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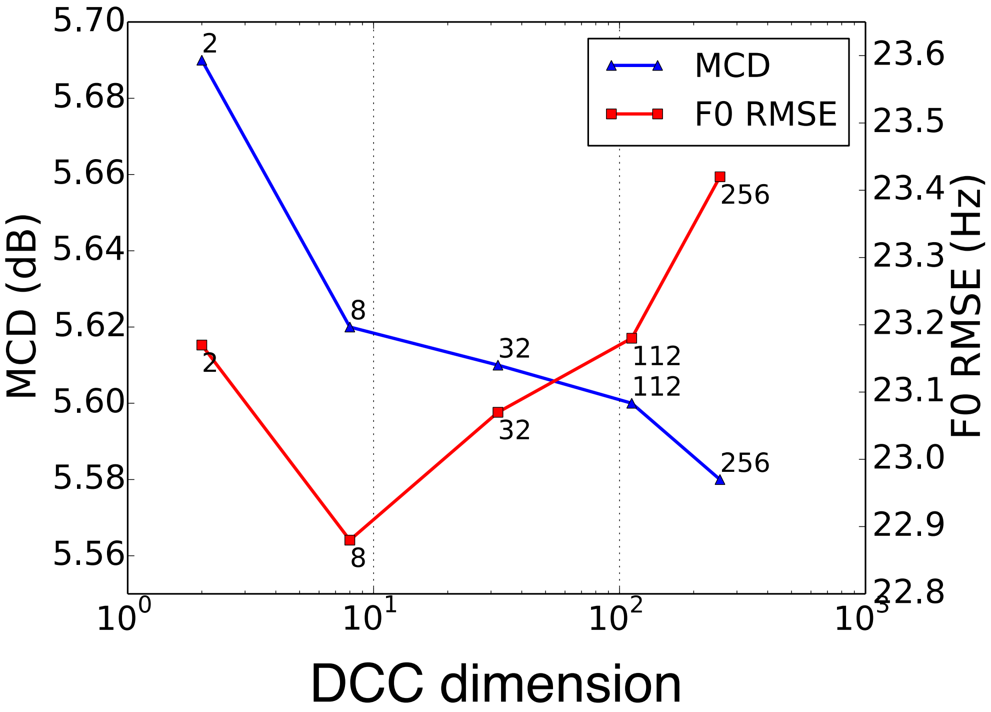

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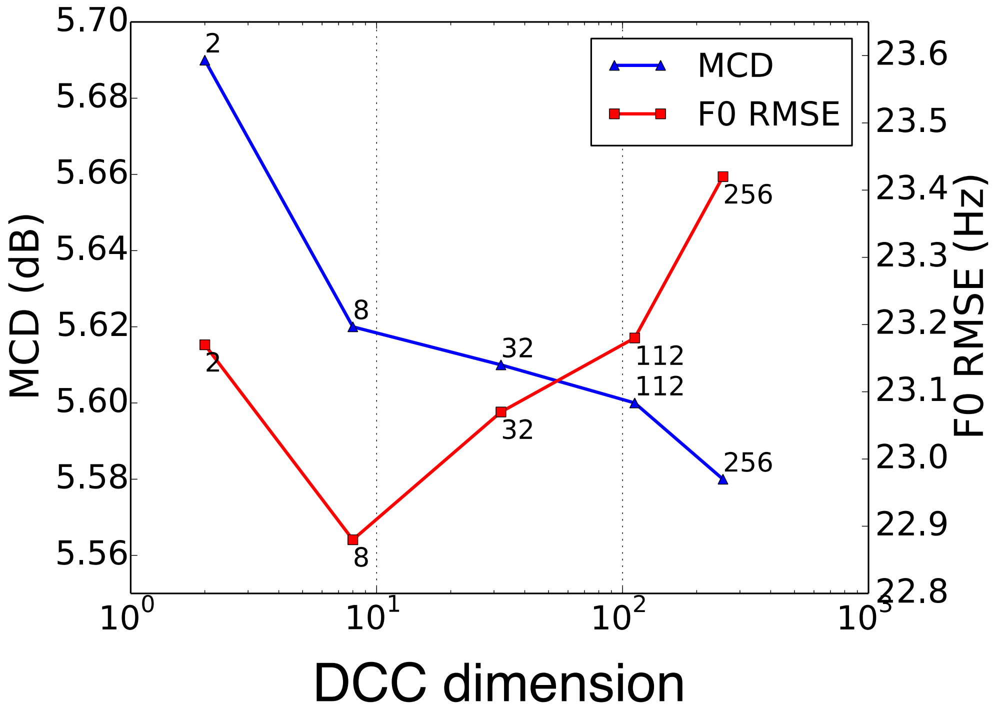

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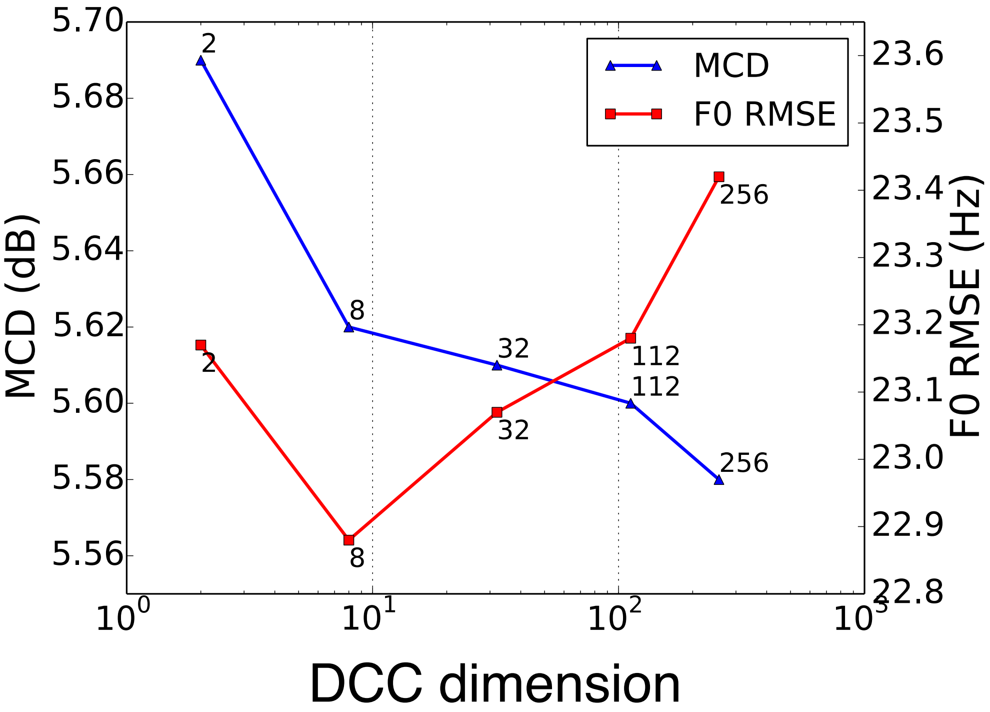

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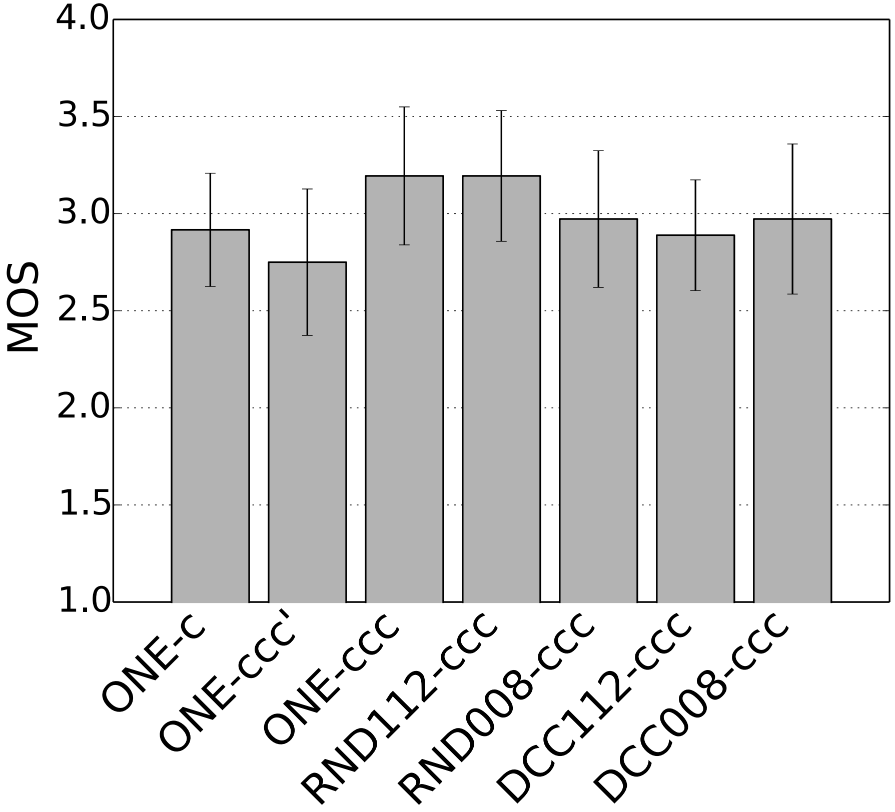

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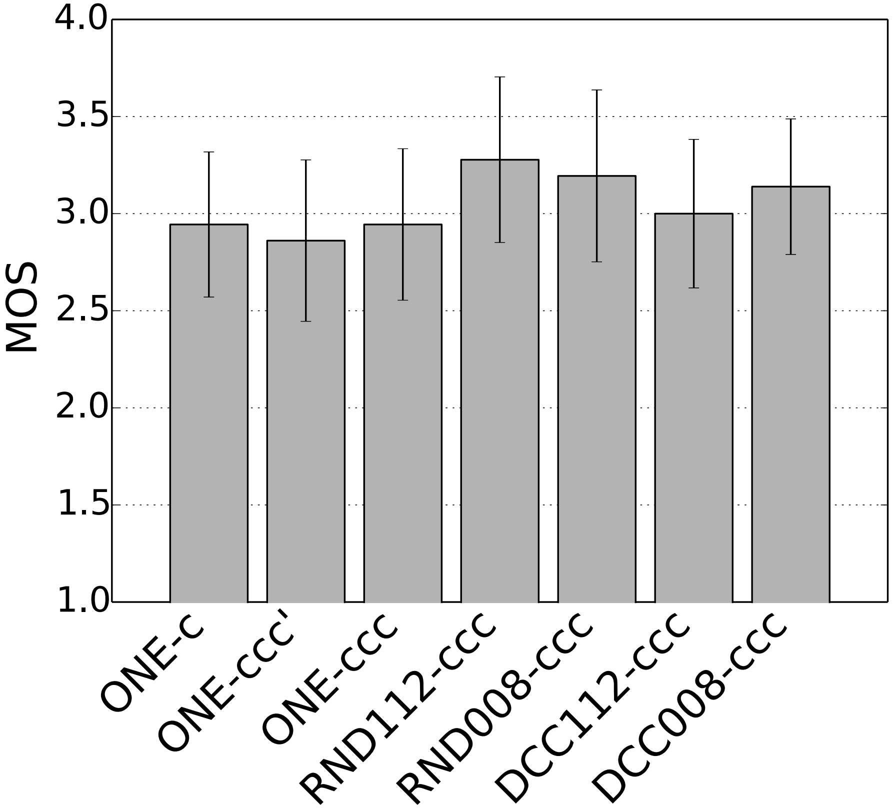

Speaker similarity

– No significant differences

– Tested code representations have similar performance

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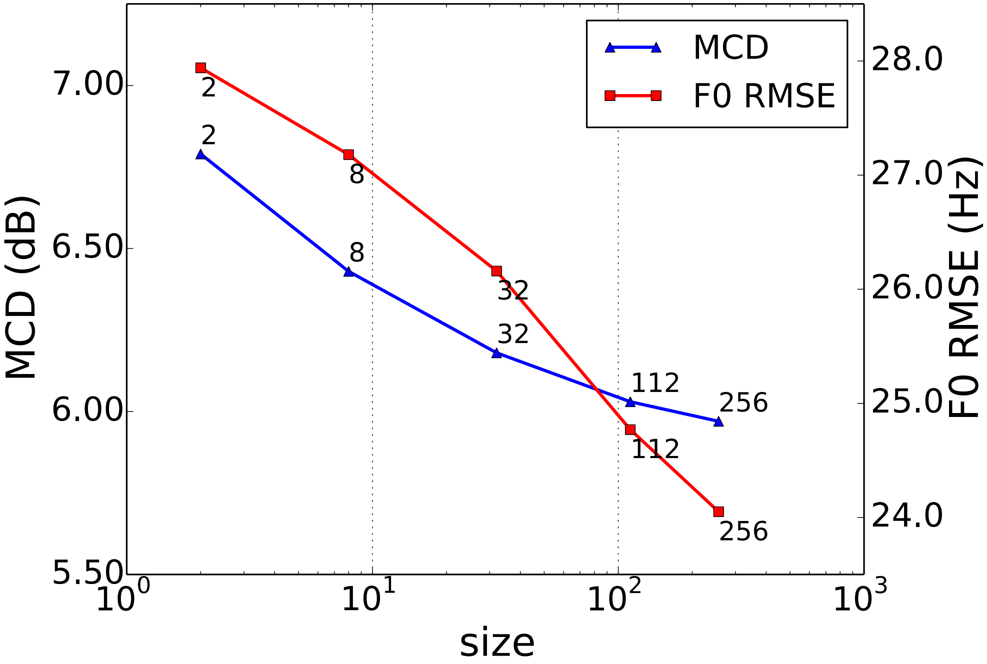

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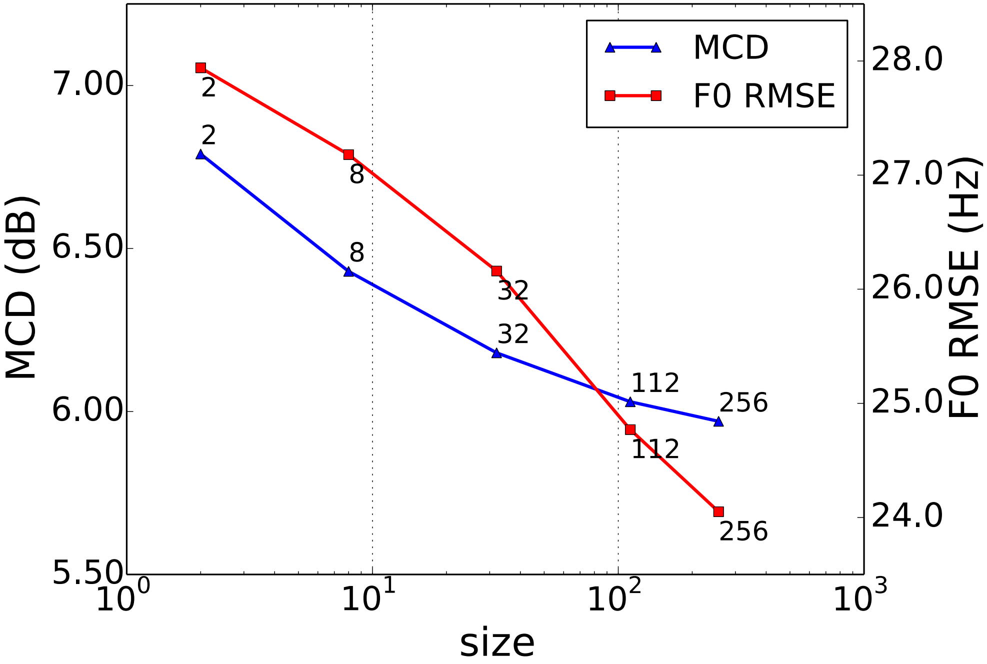

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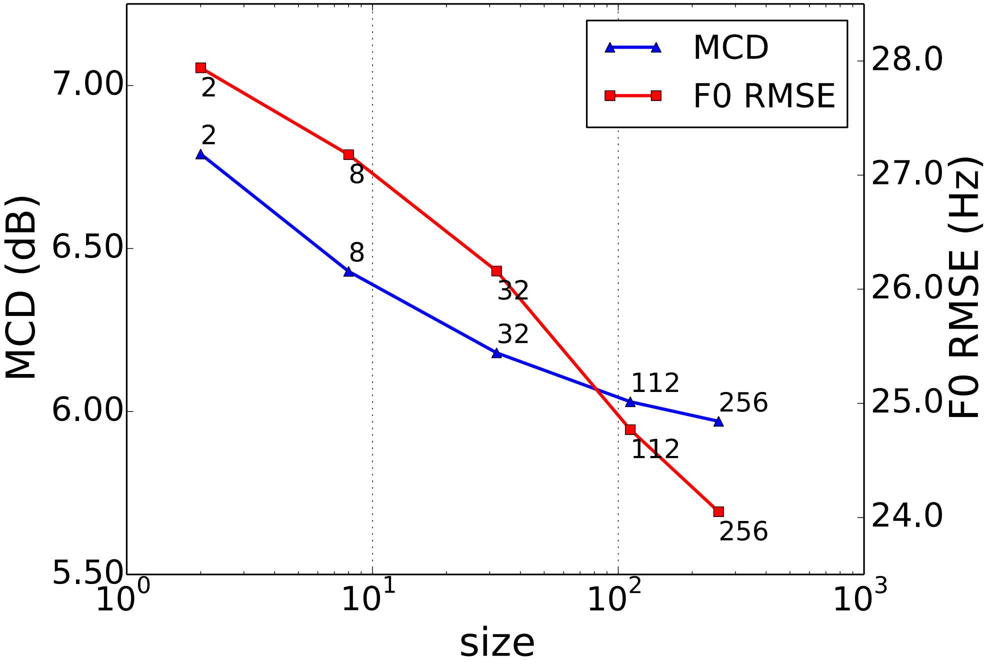

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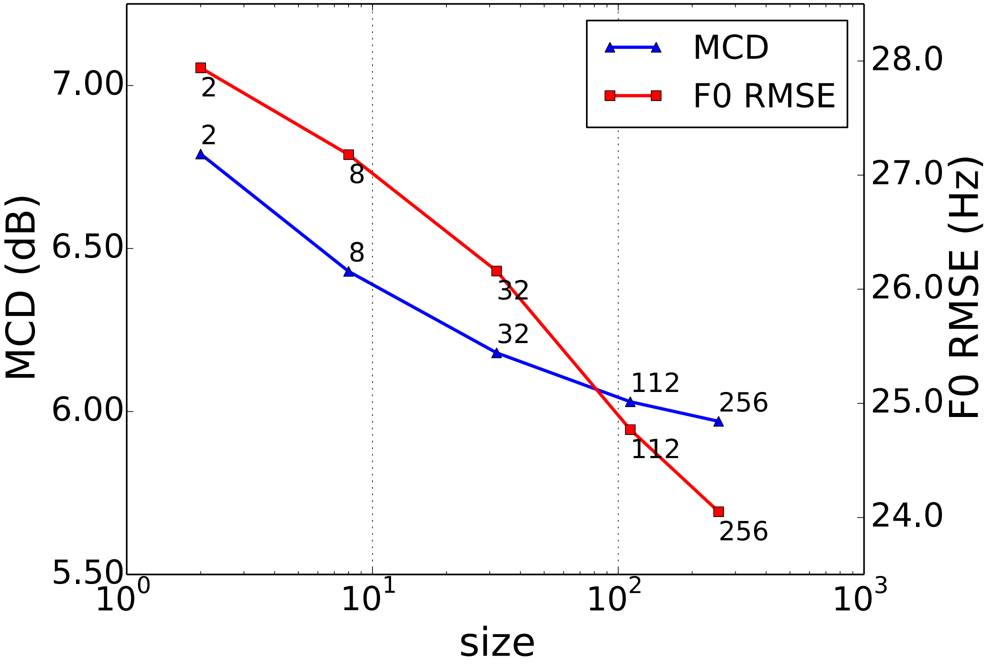

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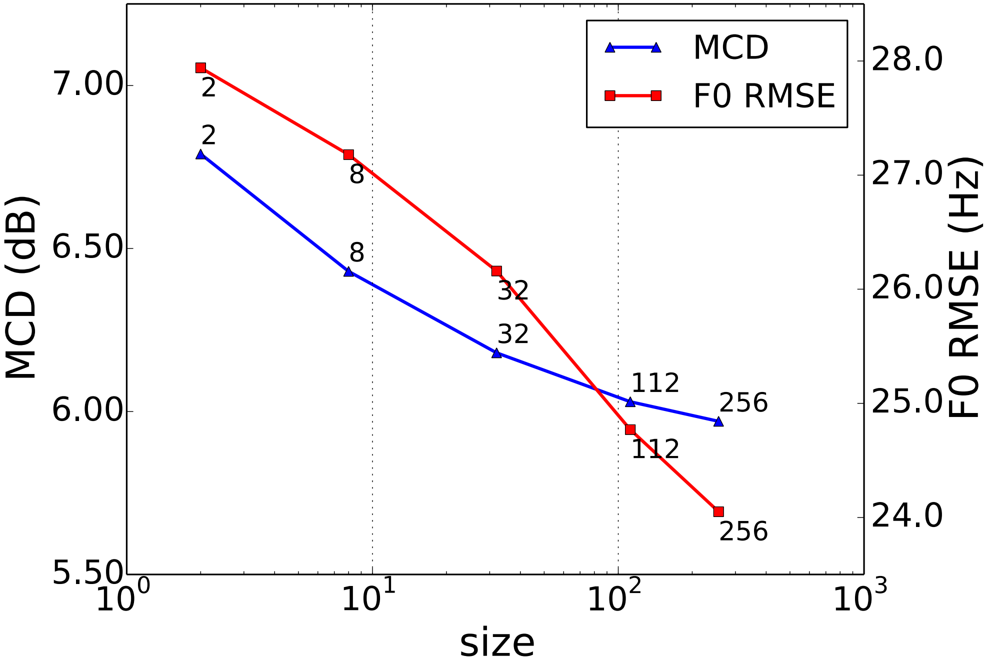

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Adaptation speakers (unknown)

– Known speakers: **5.6 dB**, unknown speakers: **6 dB**

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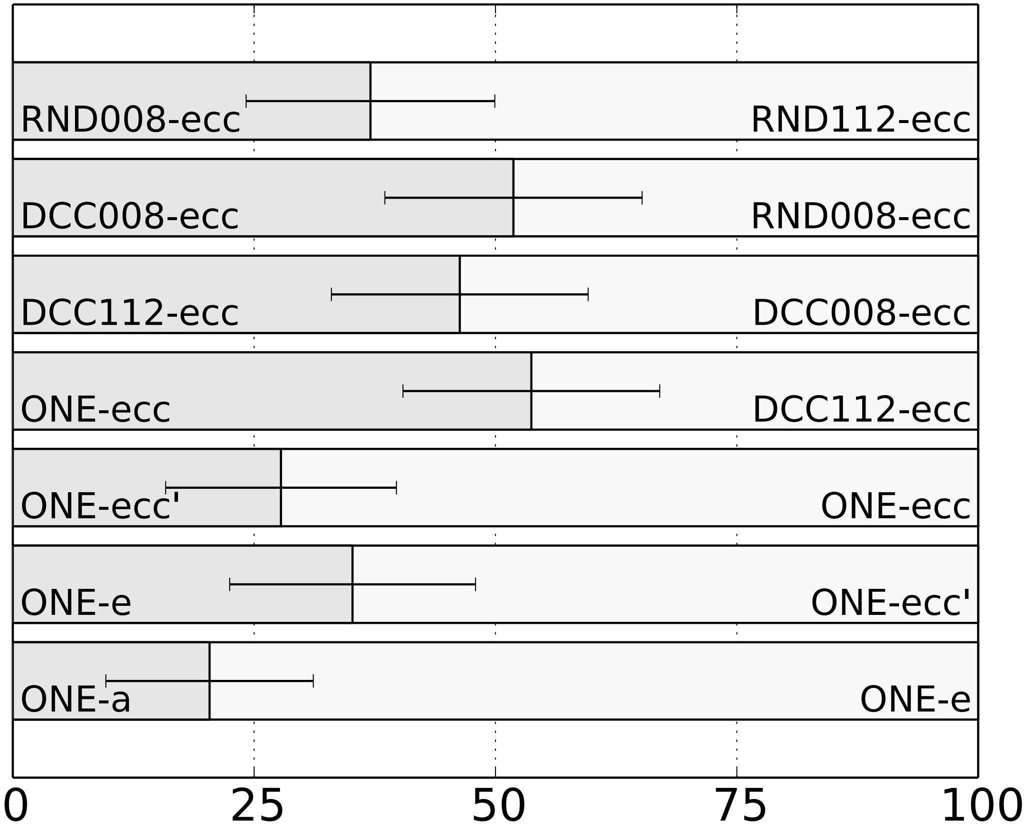


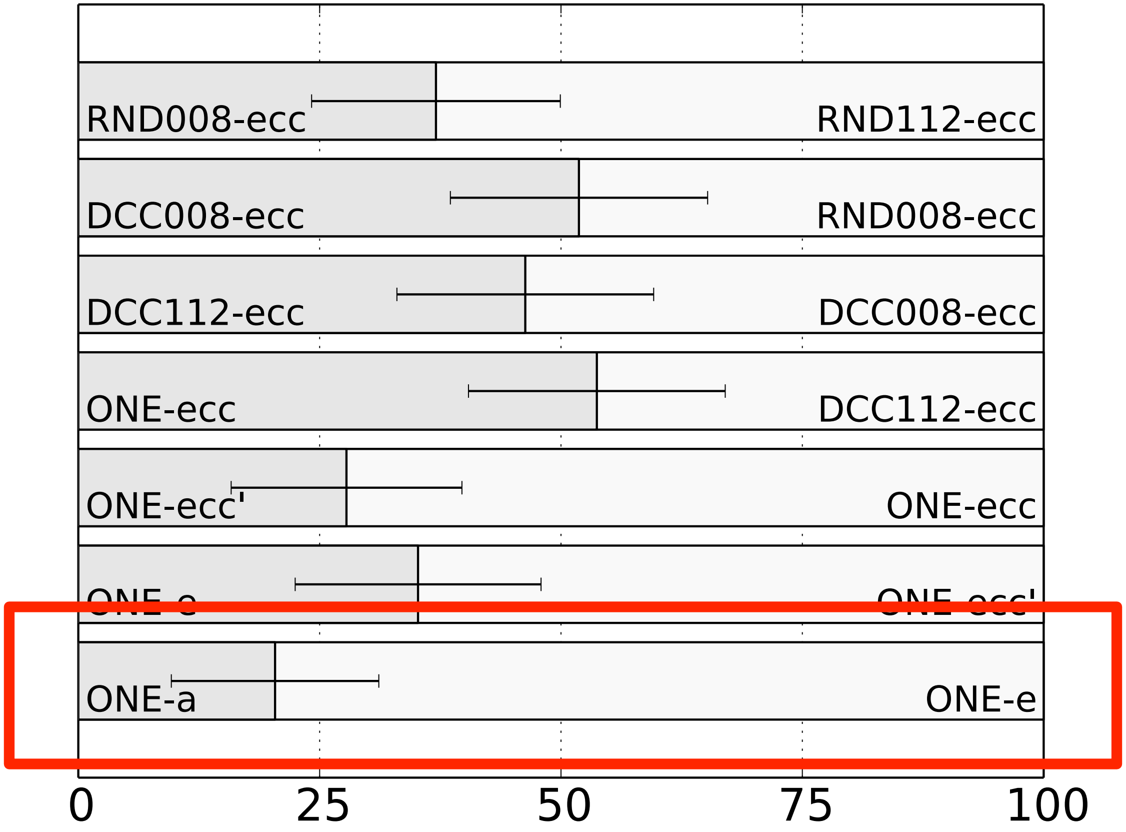
– Speaker similarly judgement via AB test

– Estimated codes have more similarity than average code

– Using gender and age codes improves speaker similarity

– Numeric gender/age representation is better

# Subjective evaluation: AB test, adaptation



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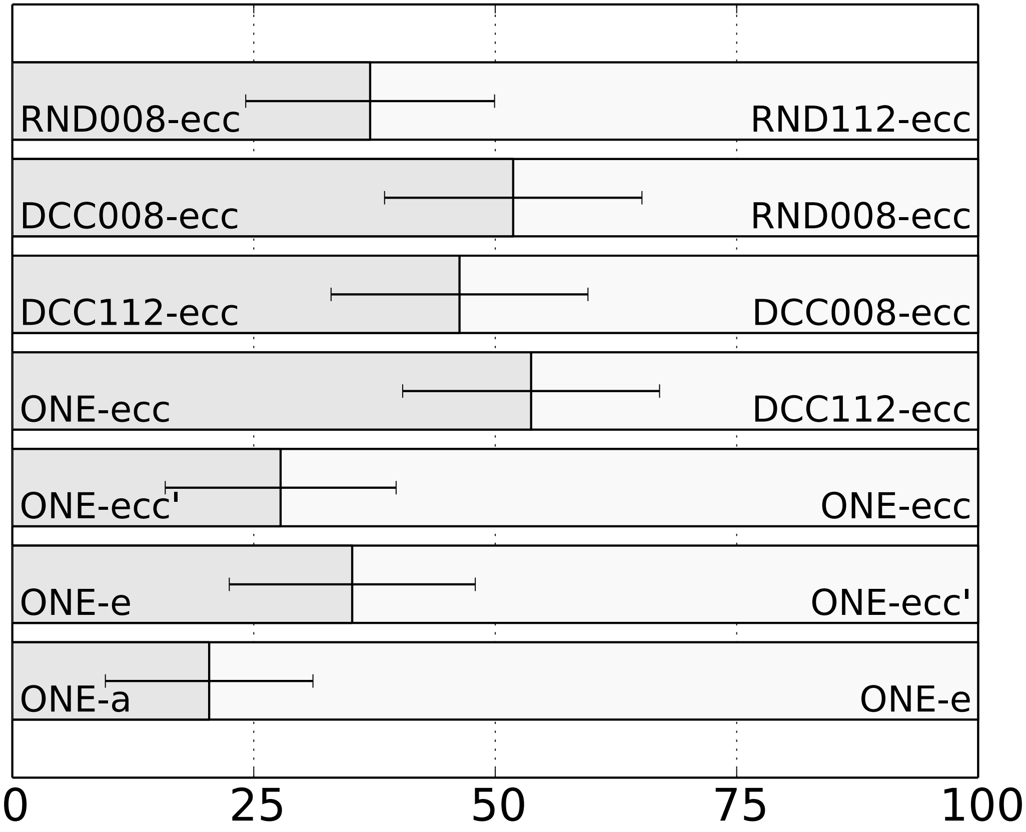

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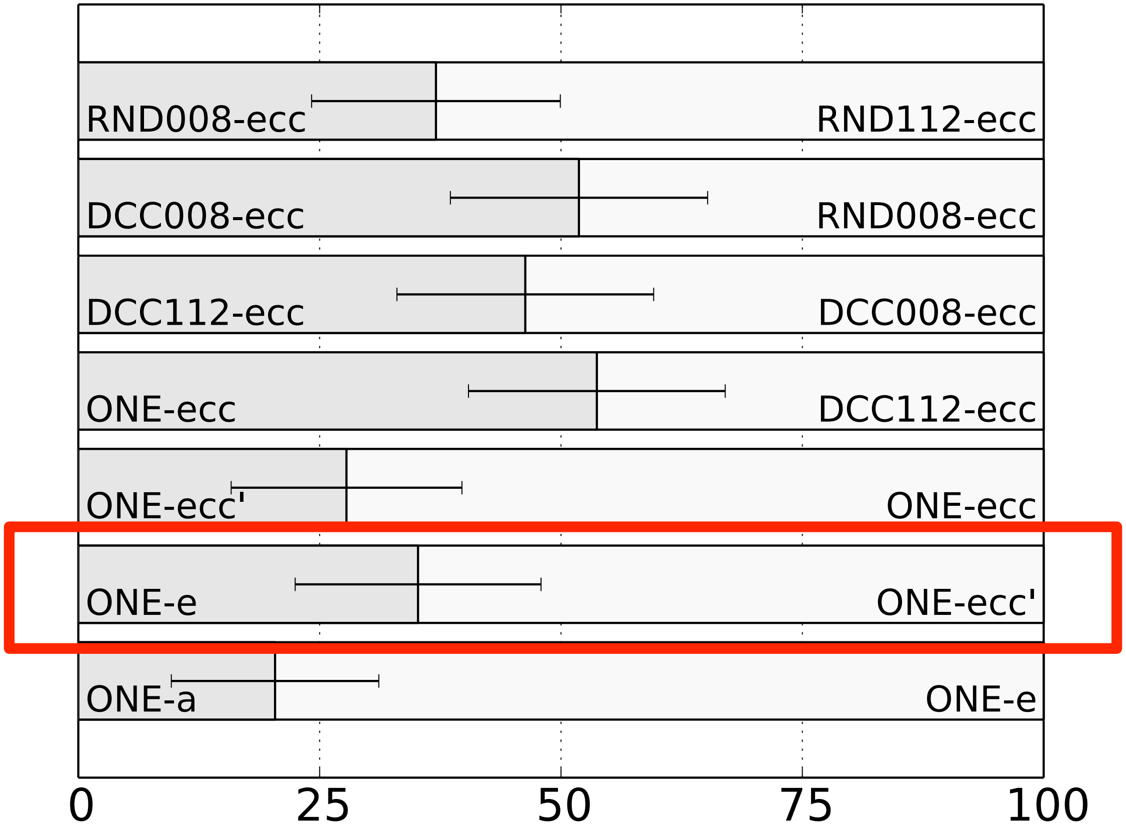

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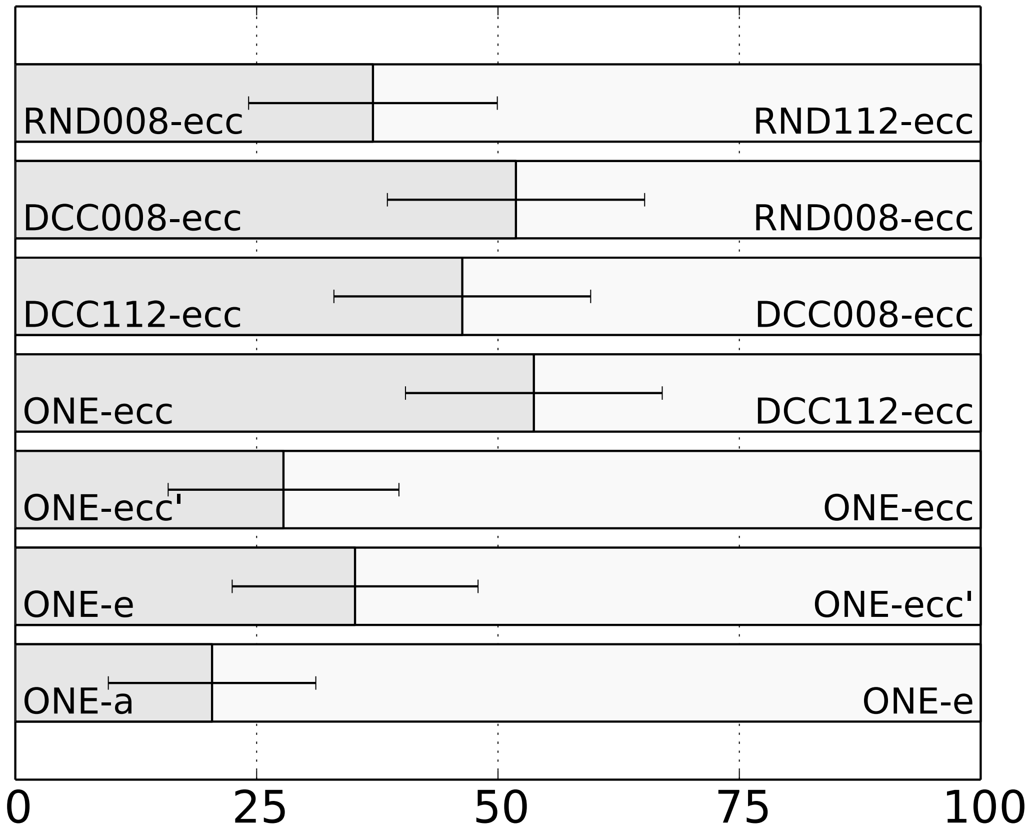

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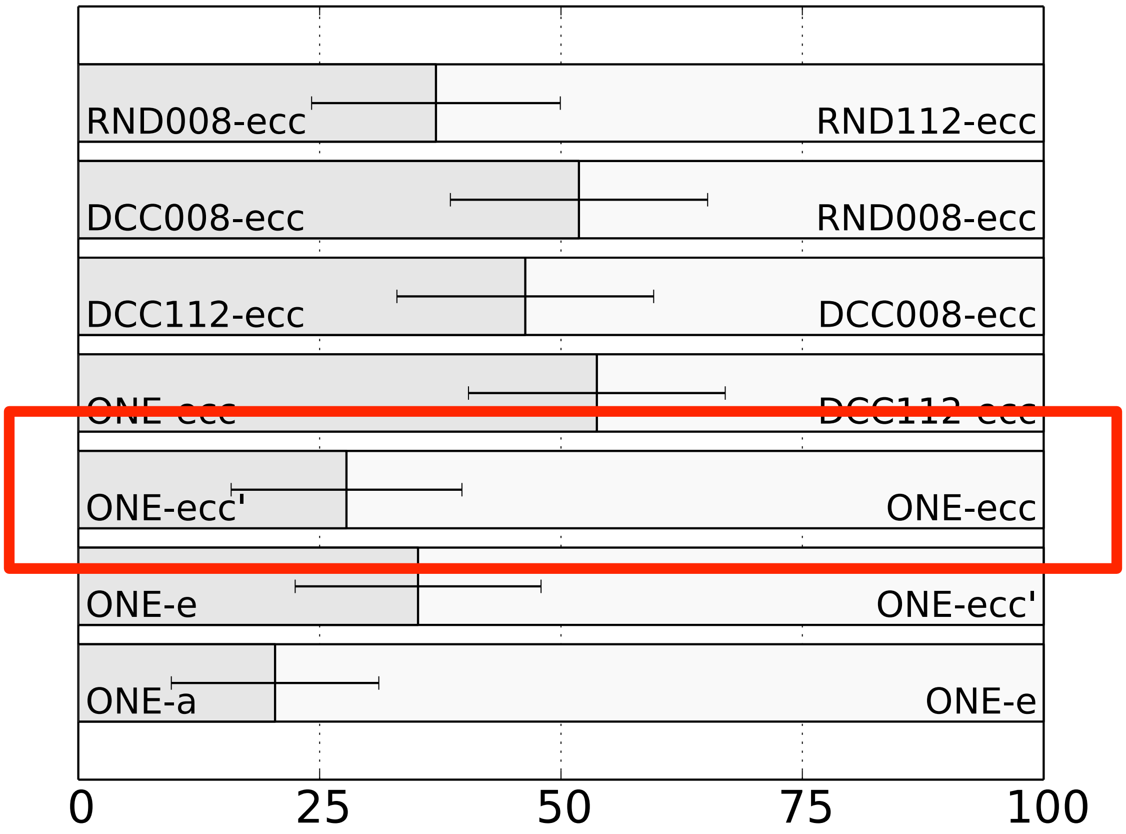

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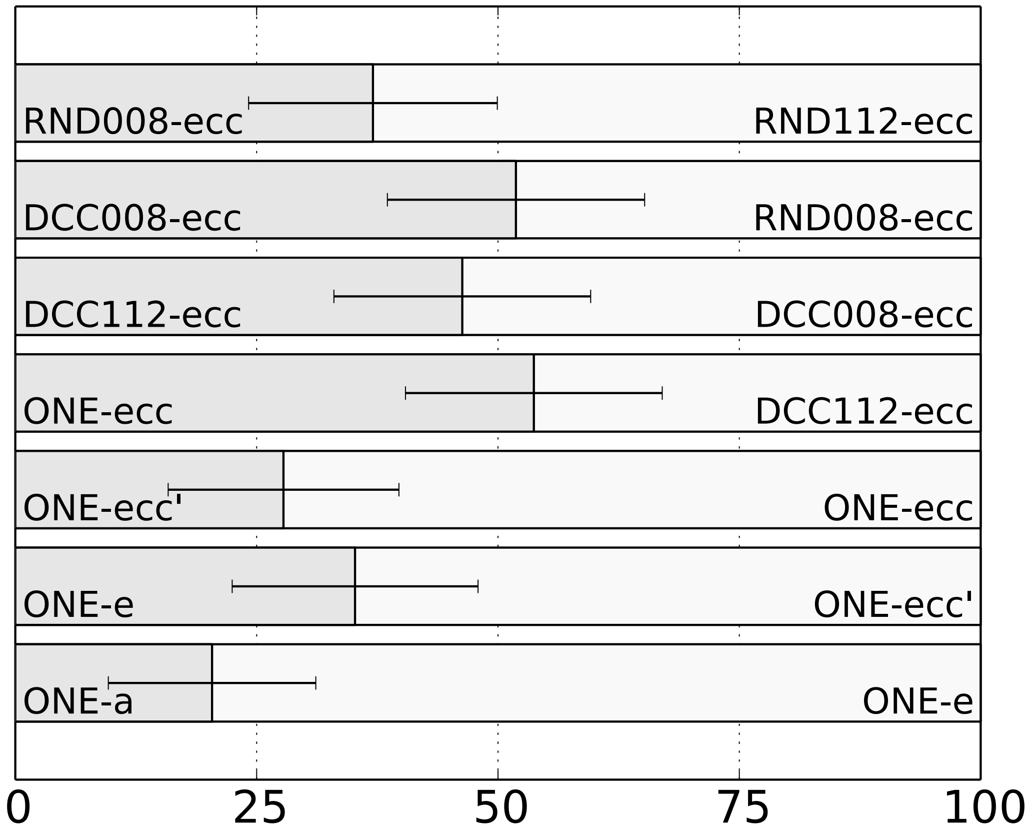

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# Demonstration

## Speaker adaptation

| Target | One-a | One-e | One-ecc |
|---|---|---|---|
| | | | |
| | | | |

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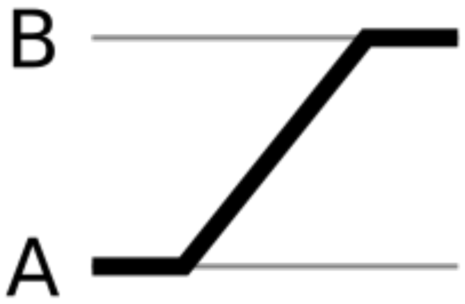
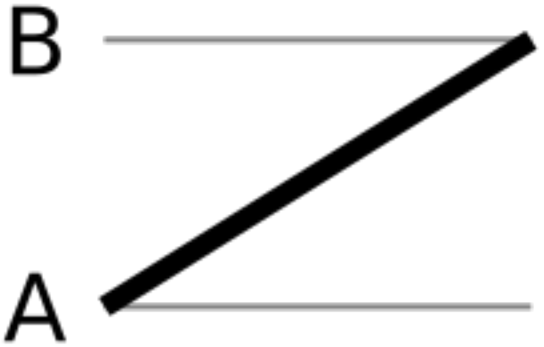
# Demonstration

Speaker interpolation



Gender morphing



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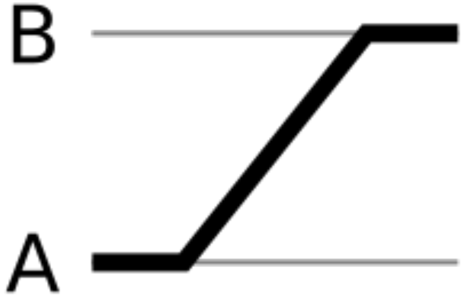

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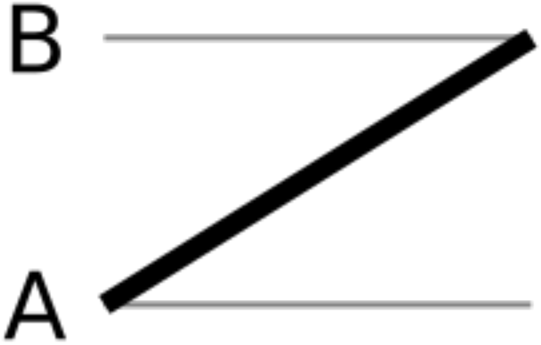

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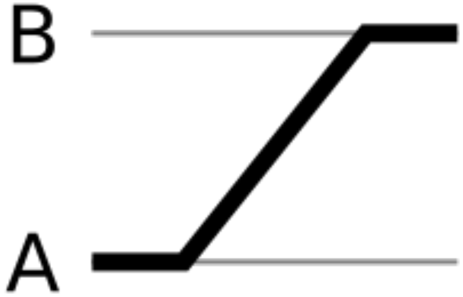

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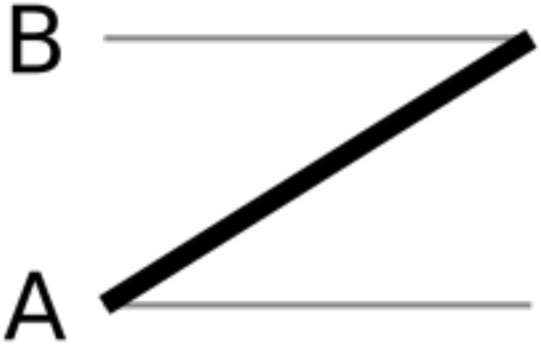

# Conclusions

## DNN speech synthesis systems using input codes

- Multi-speaker modelling
- Speaker adaptation
- Manipulation and control

Large-scale speech database
Objective and subjective tests

- **Flexible DNN speech synthesizers**
  - Input codes seem to be effective
- Gender and age codes
  - Improve speaker-adaptation performance
  - Similar finding to HMM-based speaker adaptation

## Future work

- Evaluation using LSTM-RNN and waveform models
- Improved adaptation methods
- Investigate different input codes

# Other inputs codes that we're investigating

## Emotions

RNN-based audio examples where emotions are manipulated using emotional codes

## Speaking skills

Voice talent, semi voice talent, amateur

Annotations of hundreds of speakers completed

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Thank you very much

Q&A

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