Customization of IBM Intu's Voice by Connecting Text-to-Speech Services with a Voice Conversion Network

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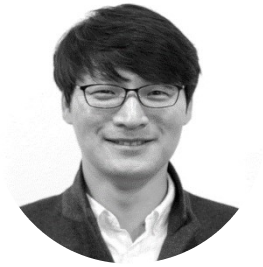
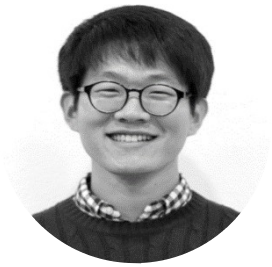

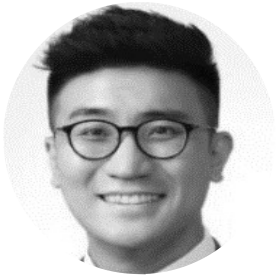


HICSS IBM VERI LUX TAS MEA

Outline

- Introduction
- Related Work
  - IBM Watson and Project Intu
  - Text-to-speech (TTS)
  - Voice conversion
- Model Description
  - Voice conversion network (VCN)
  - Intu
- Experiments and Discussion
- Conclusion

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Introduction

- Intelligent Personal Assistant
- Artificial Intelligence Speaker

Amazon Echo [1]

Google Home [2]

Apple Siri [3]

Introduction

Preset voice

Introduction

Customized voice

Introduction

Customized voice

Voice customization
= easy for users to train

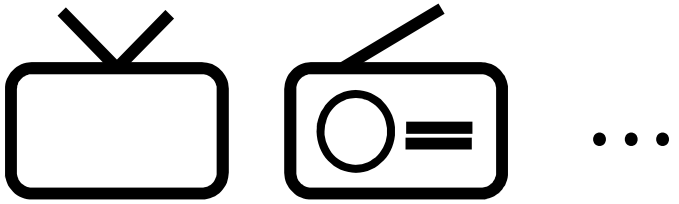
Introduction

Customized voice

Voice customization
= easy for users to train

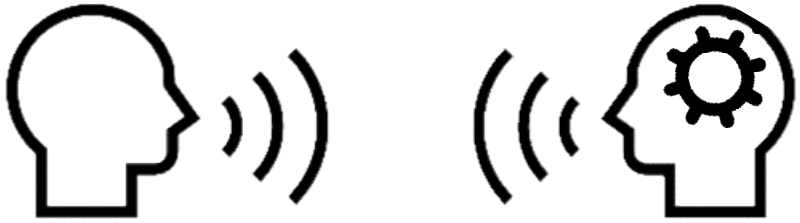
Our design
- Small target speech data
- No parallel data

Introduction



1. Gather 10~ min of speech of preferred voice

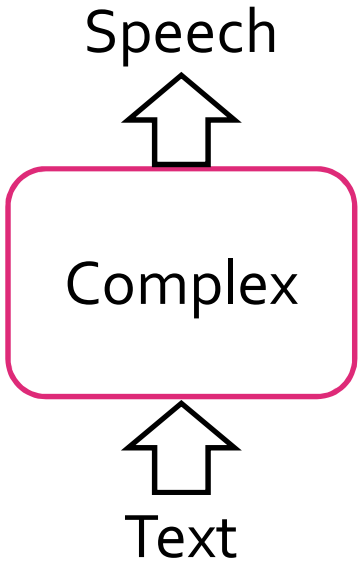
2. Send to Intu to train voice customization module



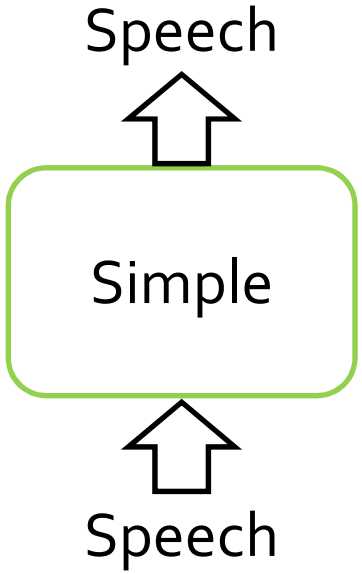
3. Users can talk with AI speaker with customized voice

Introduction

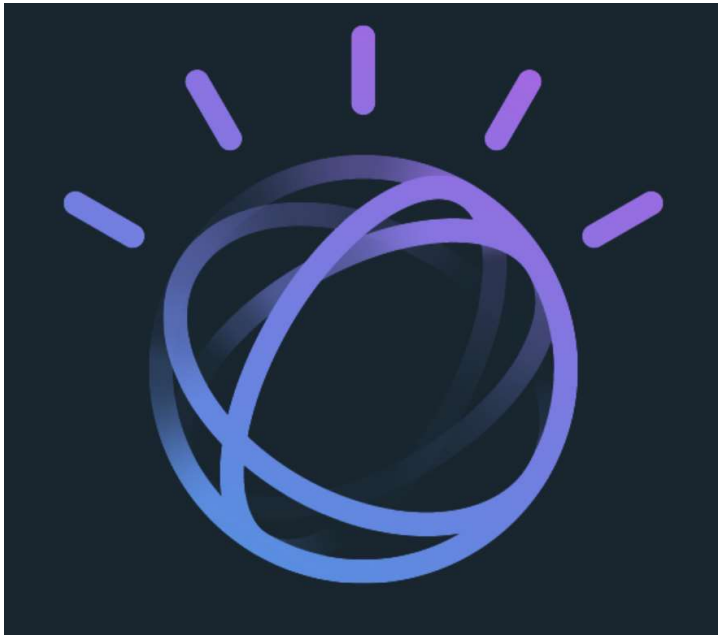
- Text-to-speech (TTS)
  - Text : linguistic & phonetic feature
  - Speech : phonetic & acoustic feature
  - Requires relatively complex model
  - Needs around 30 min of speech per voice [4]

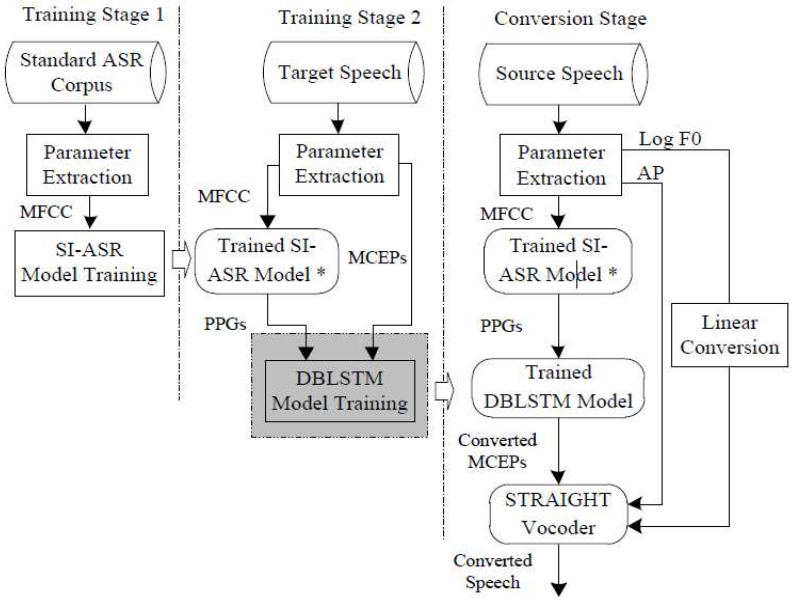


- Voice conversion
  - Inputs and outputs have same feature domain
  - Requires relatively simple model
  - Needs around 10 min of speech per voice [5]



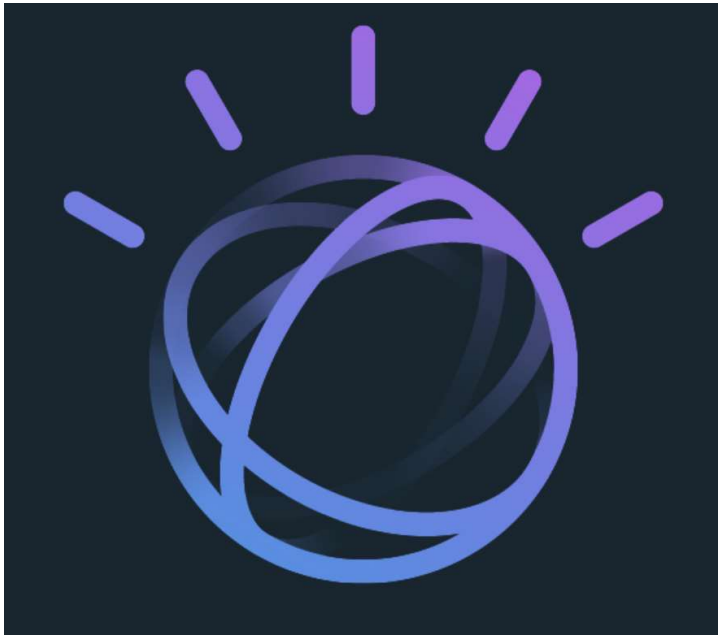
Introduction

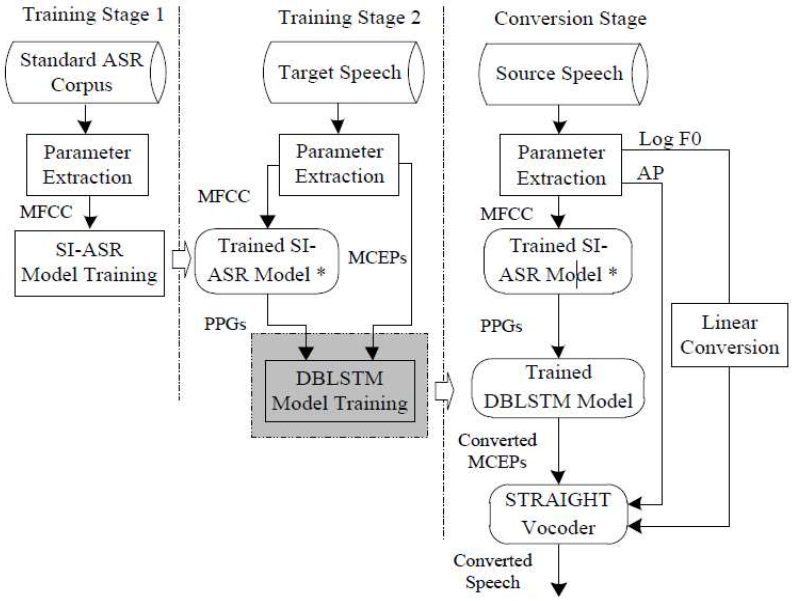




Project Intu [6] + Voice conversion [5]

Introduction



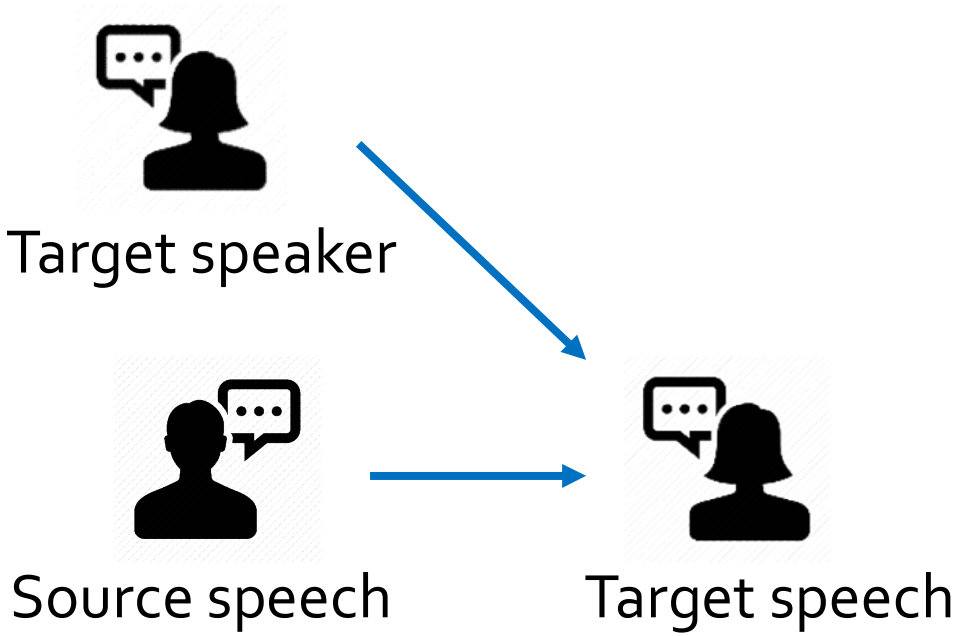


Pre-trained using public speech data

+

Trained using 10~ min of target speech

Introduction



- Source speaker/speech

The speaker of voice before conversion / the speaker's speech

- Target speaker/speech

The speaker whom the user prefers / the speaker's speech

Contribution

- Voice customization for ML-as-a-Service design
- Methods for inference time optimization
- Analysis for proper amount of target speech

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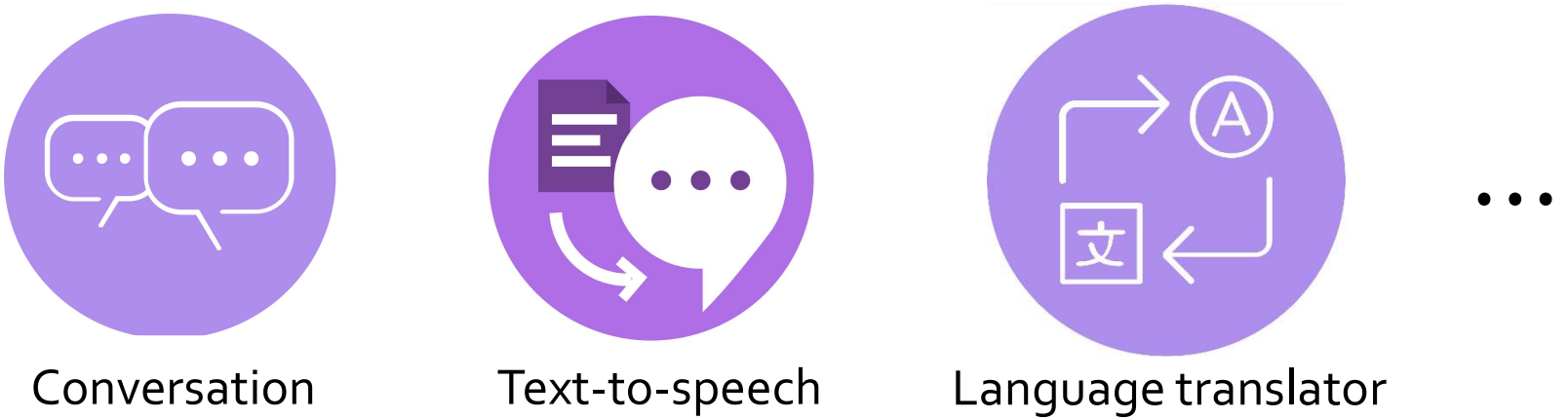
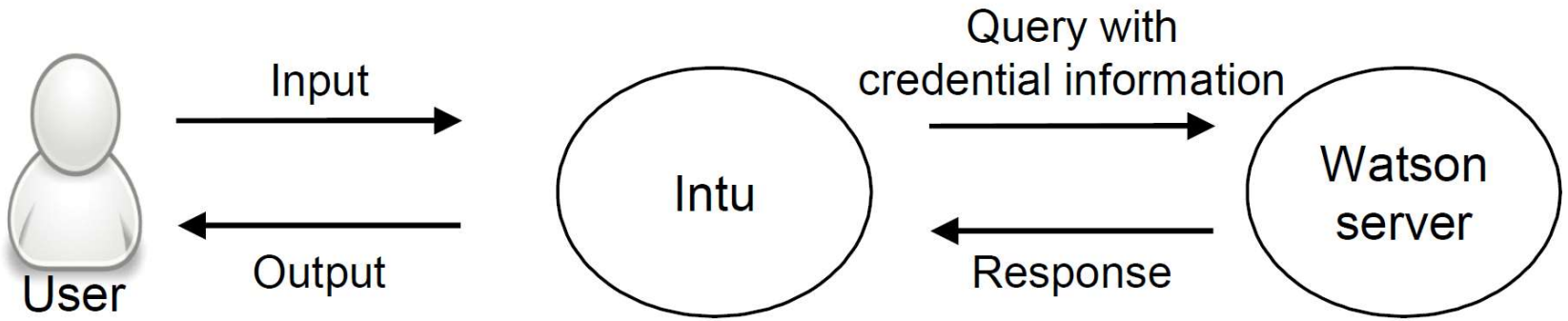
Related Work – IBM Watson and Project Intu

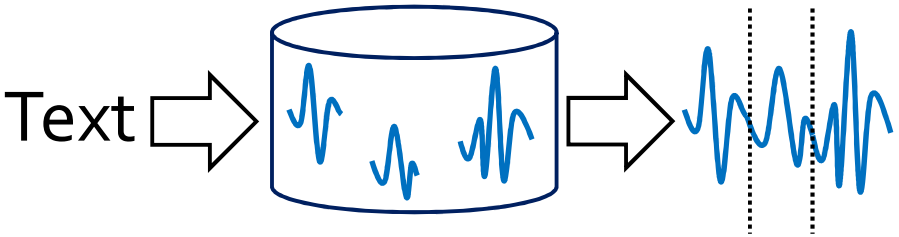
- IBM Watson : API service for cognitive task



- Project Intu : A platform for intelligent personal assistant service

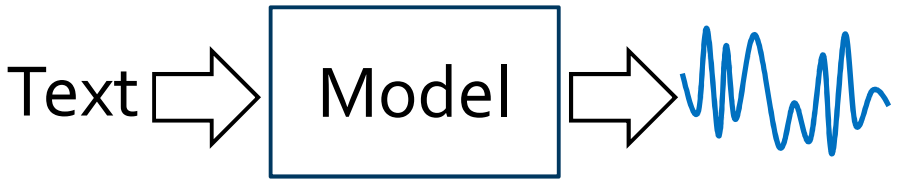


Related Work – Text-to-speech



Unit selection

- Decision tree [7]
- Recurrent Neural Network (RNN)
  - IBM Watson's text-to-speech [8]



Parametric generation

- Hidden Markov model [9]
- Dilated convolution neural network
  - WaveNet [4]

  Recurrent Neural Network (RNN)
  - Deep Voice [10]

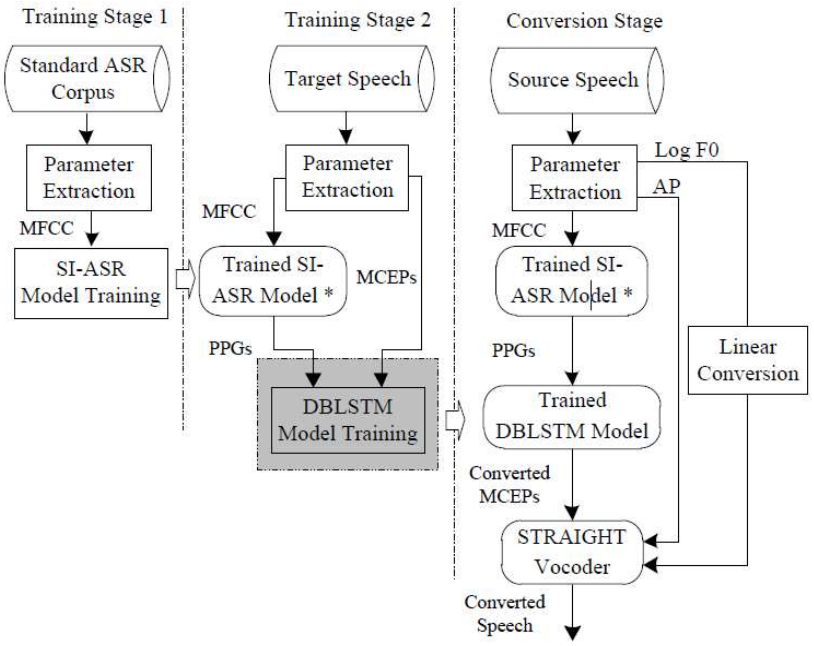
Related Work – Voice conversion

Training data	One-to-one w/ parallel data	→	Many-to-one w/ parallel data	→	Many-to-one w/o parallel data
Model	Codebook [11]	→	Gaussian mixture model [12]	→	Boltzmann machine [13] Deep belief network [14] → RNN [5]

Lifa Sun et al., 2016 [5]

- Multi-layer bidirectional RNN is used
- Both input & output are from target speech

⇒ No parallel data and alignment issue



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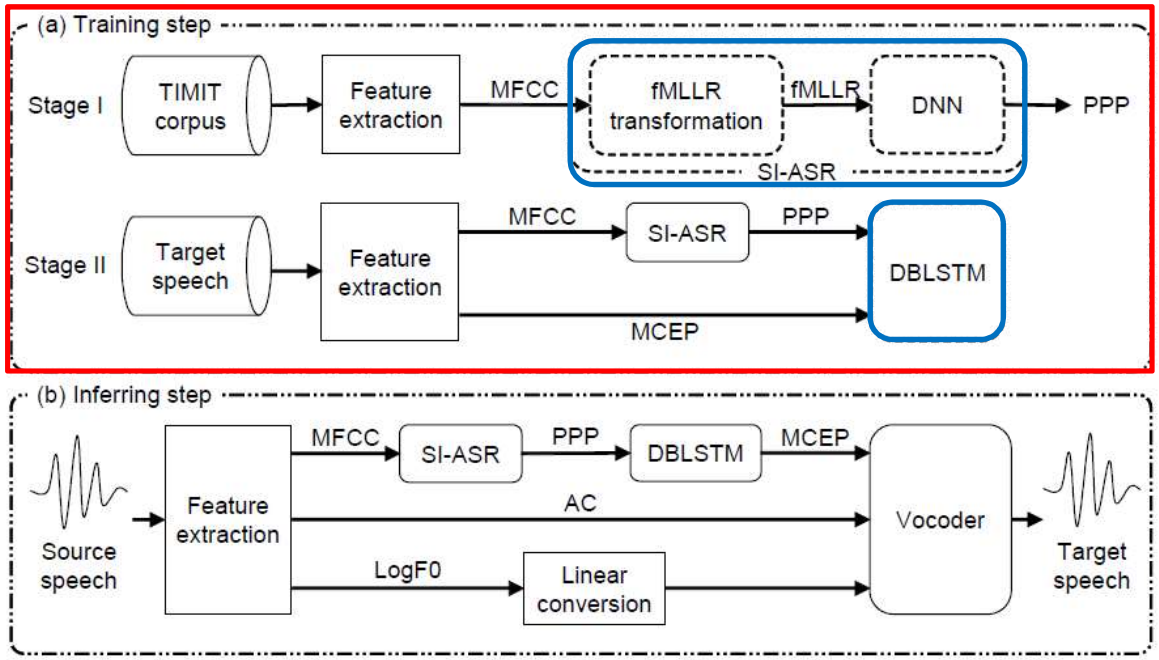
Model Description – Voice conversion network (VCN)

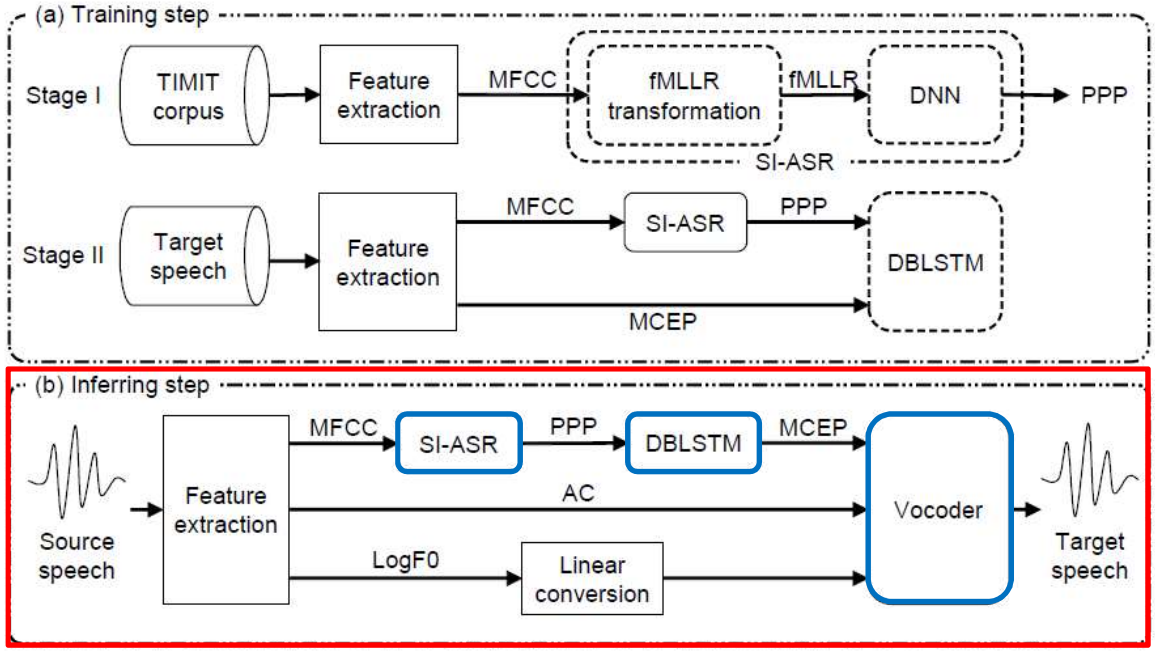
- Overall structure of VCN



- Training step
  - Stage I : raw wave → linguistic feature
  - Stage II : linguistic feature → target speaker's acoustic feature

Model Description – Voice conversion network (VCN)

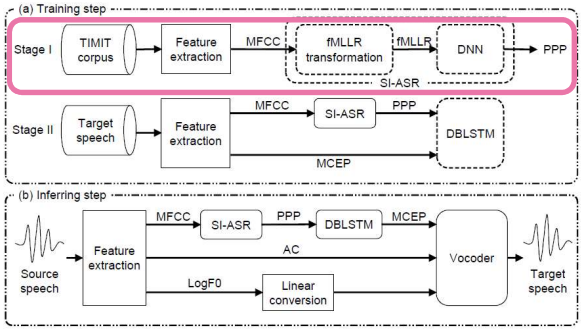
- Overall structure of VCN

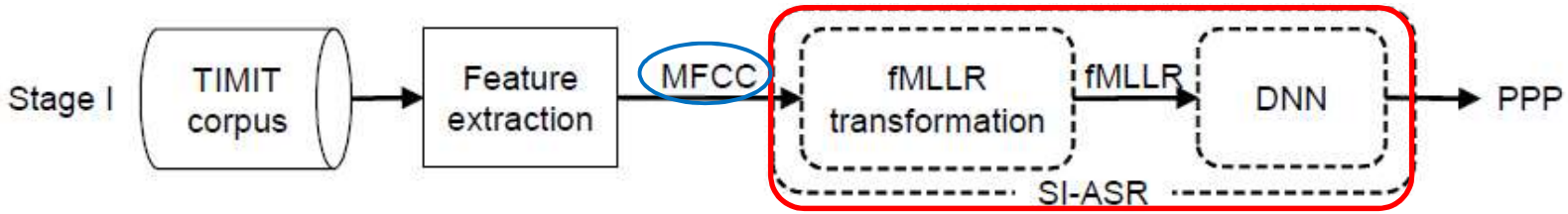


- Inferring step
  - Stage III : source speech → target speech

Model Description – Voice conversion network (VCN)

- Stage I



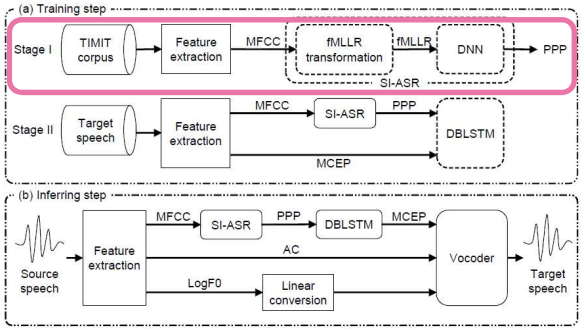


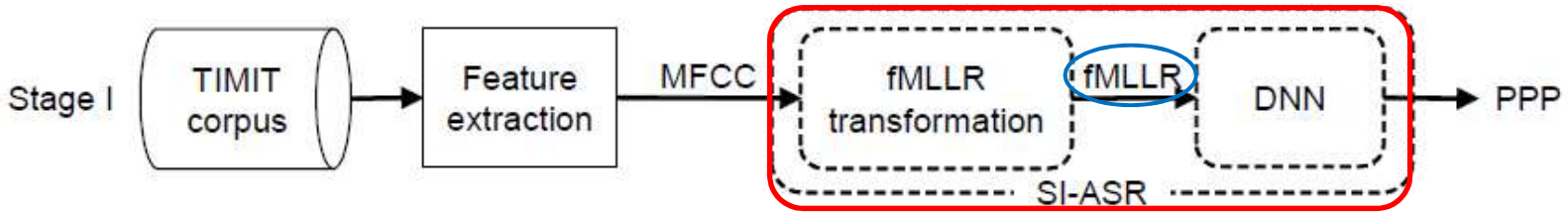
Raw wave → speaker-independent linguistic feature

- Mel-frequency cepstral coefficients (MFCCs)
  - A kind of speech's acoustic feature representation
  - Energy of each filter bank on mel-scale

Model Description – Voice conversion network (VCN)

- Stage I



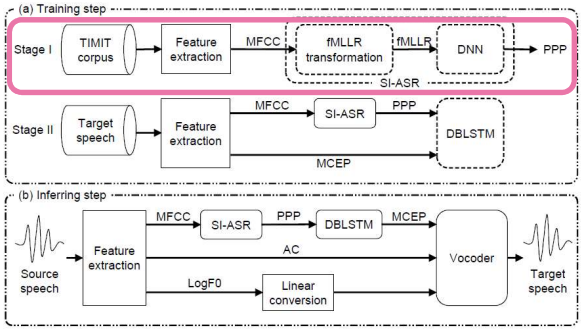


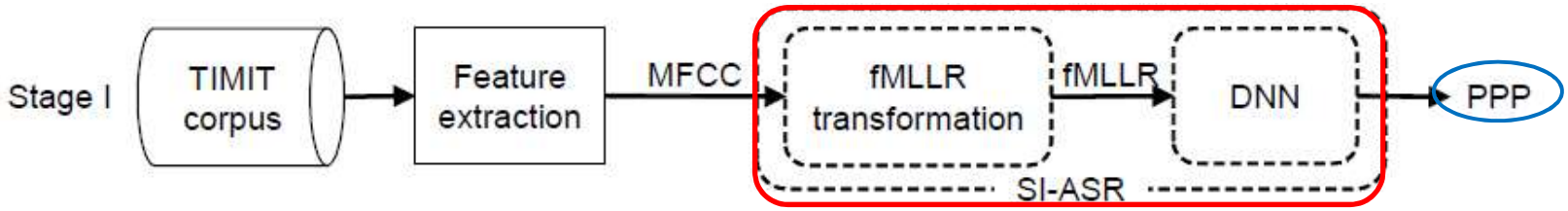
Raw wave → speaker-independent linguistic feature

- Feature-based Maximum Likelihood Linear Regression (fMLLR)
  - Speaker adaptation method transforming speech's feature vector x [15]
  - Finds affine transformation weight W maximizing likelihood of the speech

Model Description – Voice conversion network (VCN)

- Stage I





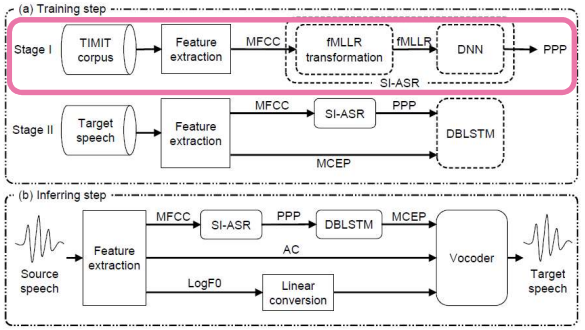
Raw wave → speaker-independent linguistic feature

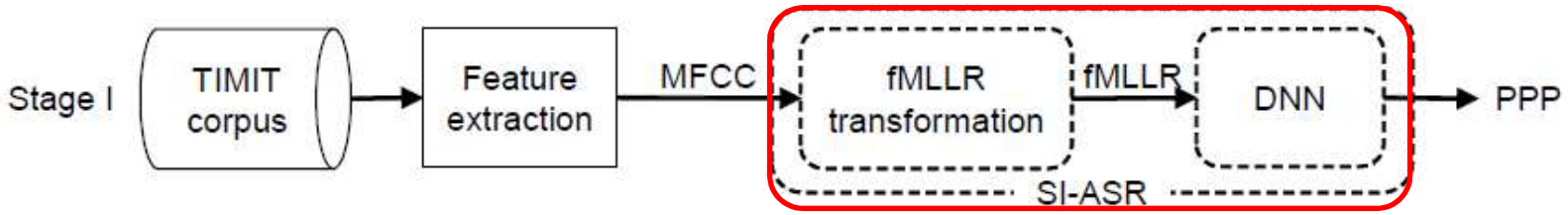
- Phonetic Class Posterior Probabilities (PPPs)
  - Probabilities of phonetic class for each piece of speech
  - Phoneme's representation is limited
  - The number of class of triphone is too large
  - Senone is cluster of triphones which are similar

Cat
Phoneme : k, æ, t
Triphone : /kæt/

Model Description – Voice conversion network (VCN)

- Stage I



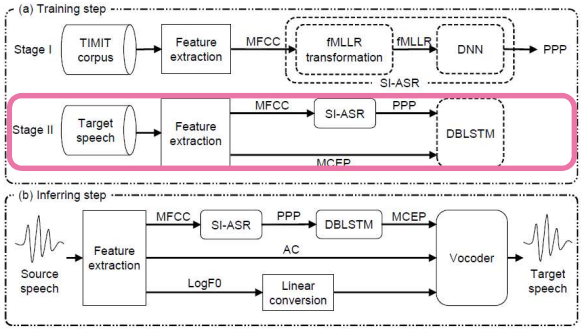


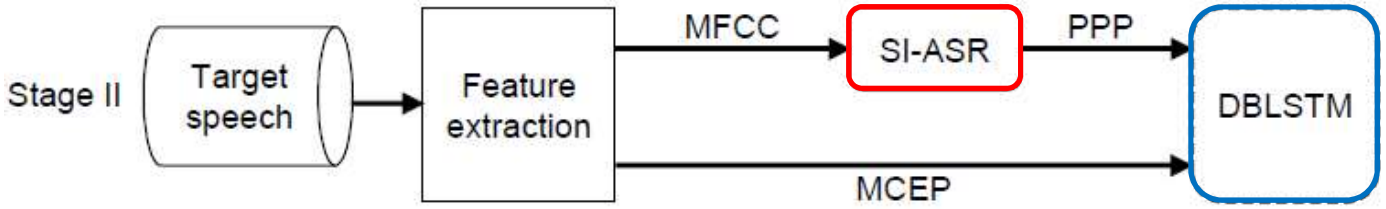
Raw wave → speaker-independent linguistic feature

- TIMIT corpus [20] is used
- MFCC, fMLLR and PPP are mapped using Kaldi toolkit [16]
- Speaker-independent auto speech recognizer (SI-ASR) maps MFCC (acoustic) feature to PPP (linguistic) feature

Model Description – Voice conversion network (VCN)

- Stage II



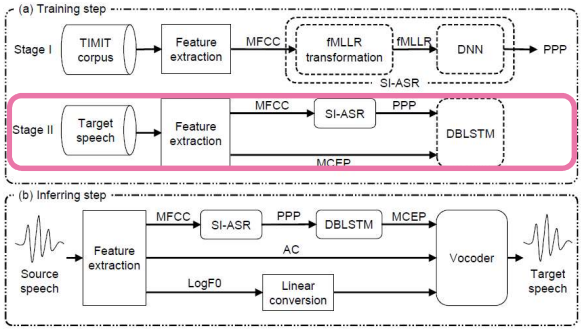


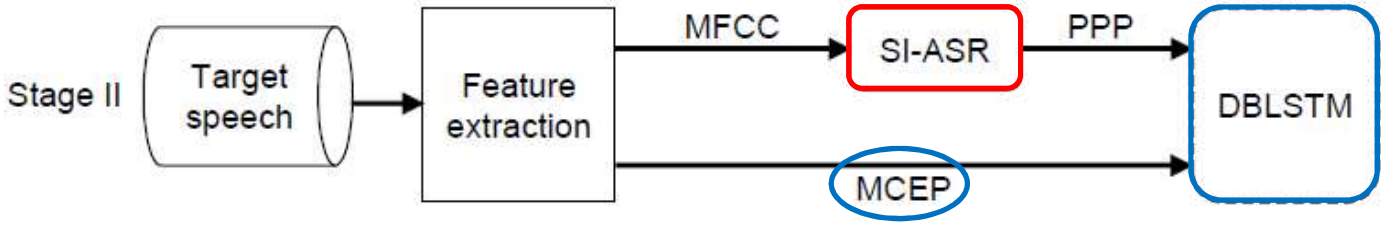
SI-phonetic feature → acoustic feature of target speaker

- Deep bidirectional long short-term memory (DBLSTM)
  - Multi-layer recurrent neural network with LSTM cell
  - It consists of forward and backward directional LSTM

Model Description – Voice conversion network (VCN)

- Stage II



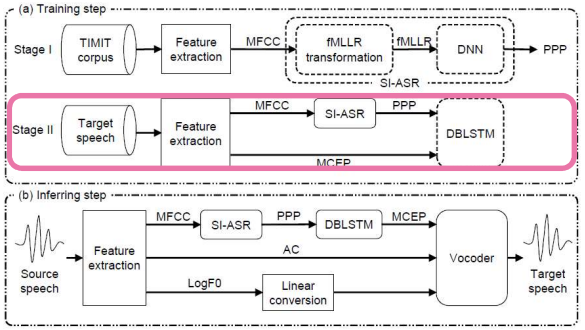


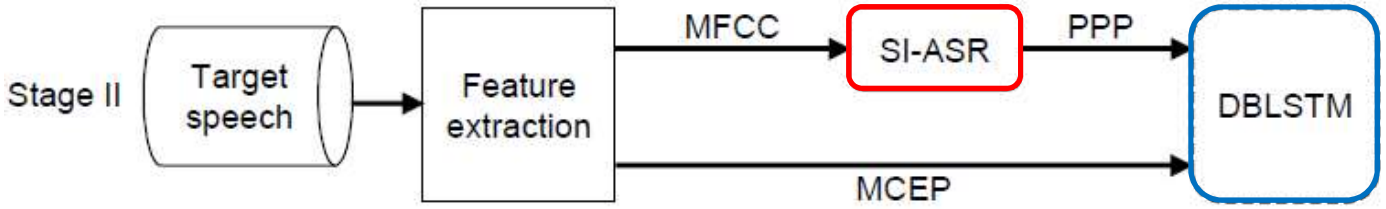
SI-phonetic feature → acoustic feature of target speaker

- Mel-cepstral Coefficients (MCEPs)
  - Another feature representation of speech
  - Mel-cepstrum analysis of spectrum $H(z)$ to find coefficients $c_\alpha(m)$ [17]

Model Description – Voice conversion network (VCN)

- Stage II



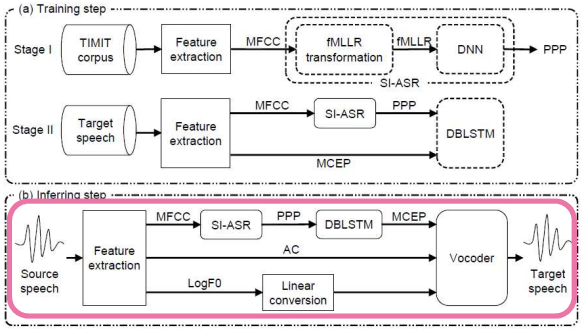


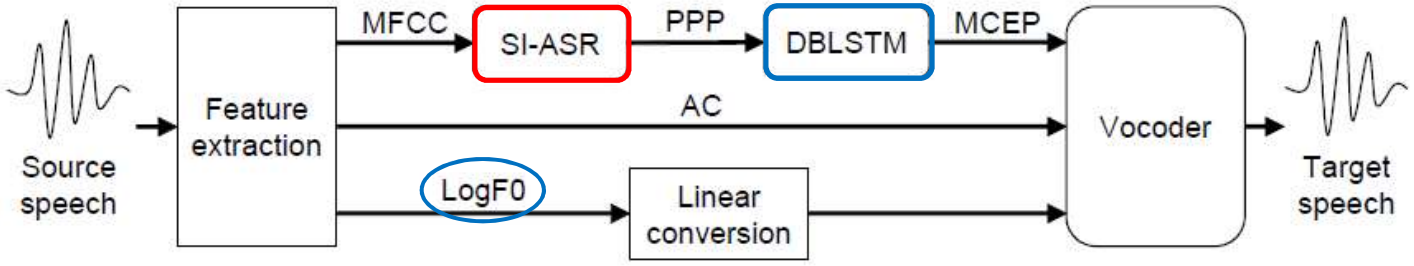
SI-phonetic feature → acoustic feature of target speaker

- Only requires target speech to achieve input and label
- Deep bidirectional LSTM model (DBLSTM) is used to map PPP (linguistic) feature to target speech's MCEP (acoustic) feature

Model Description – Voice conversion network (VCN)

- Stage III



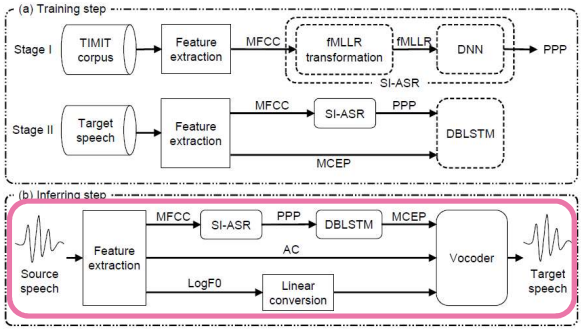


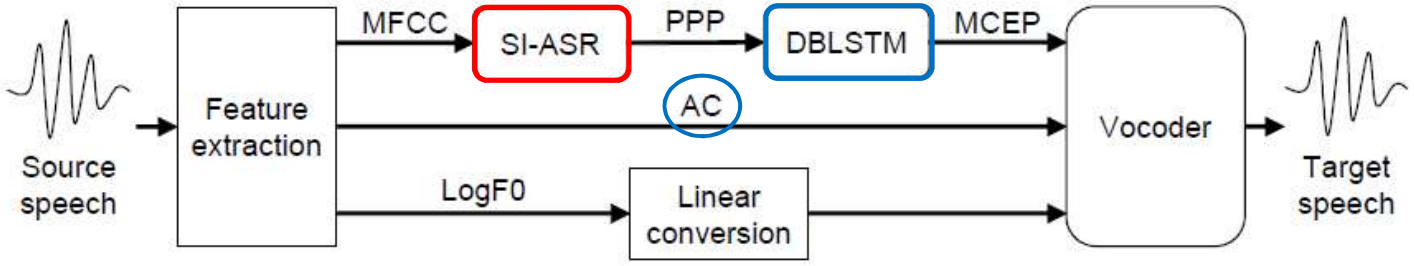
Acoustic feature → raw wave of target speech

- Fundamental Frequency (Fo)
  - Lowest frequency of a periodic waveform [18]
  - It is related with pitch of voice

Model Description – Voice conversion network (VCN)

- Stage III



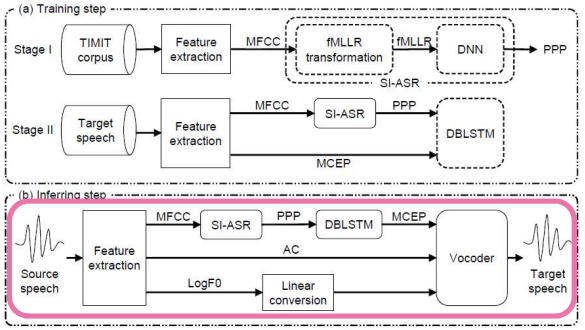


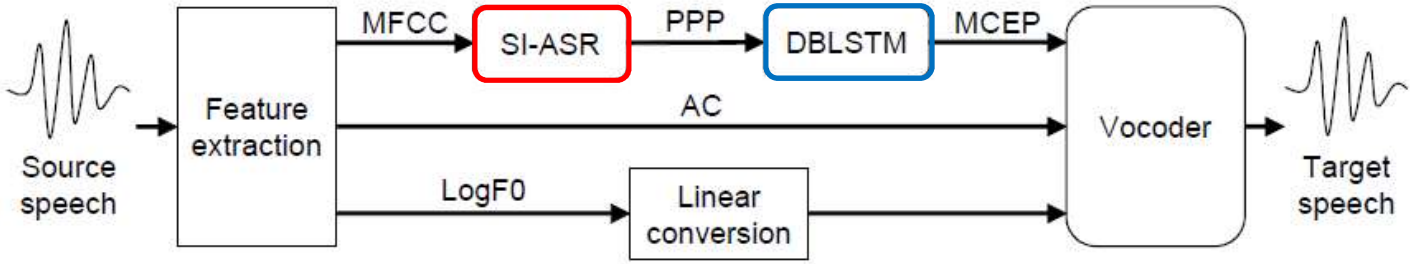
Acoustic feature → raw wave of target speech

- Aperiodicity Component (AC)
  - Non-periodic features of speech
  - It contains details of speech

Model Description – Voice conversion network (VCN)

- Stage III



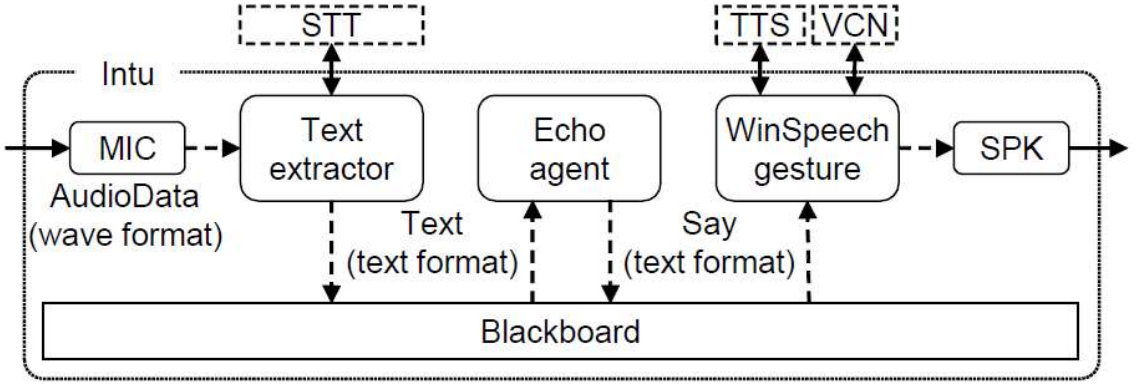


Acoustic feature → raw wave of target speech

- Whole model is achieved by pipelining the models of previous stages
- STRAIGHT vocoder [19] is used to convert acoustic features to raw wave

Model Description – Intu

- Intu structure : echoing model



(MIC) input speech
→ (Text extractor) speech to text → (Echo agent) change the type
→ (WinSpeech gesture) text to speech → voice conversion (VCN)
→ (SPK) output speech

User's speech → (Intu voice's speech) → target voice's speech

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Experiments and Discussion

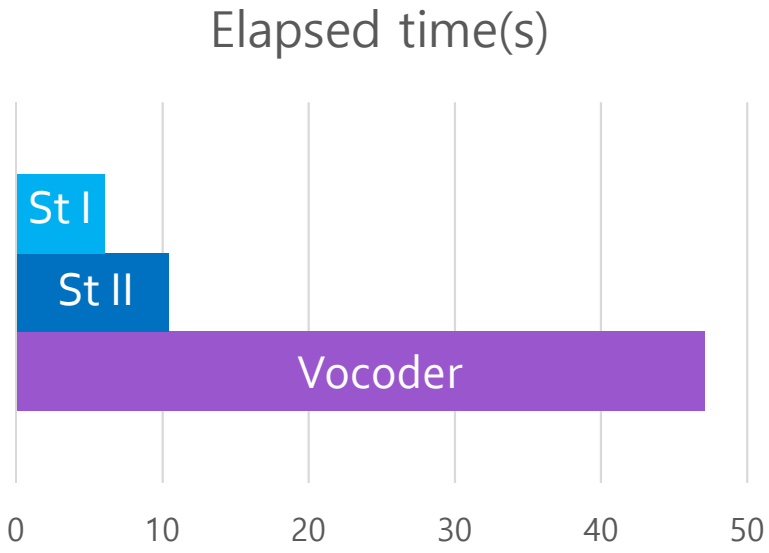
Two experiments

1. Additional **time** measurement
2. Varying **size** of the target speech samples

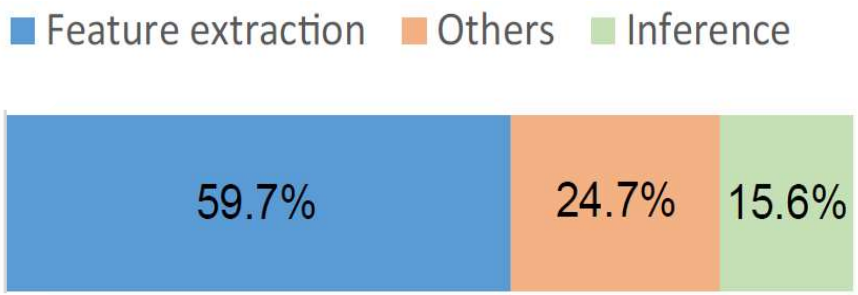
Experiments and Discussion

- Additional time measurement

Results - w.r.t step



Results - w.r.t task



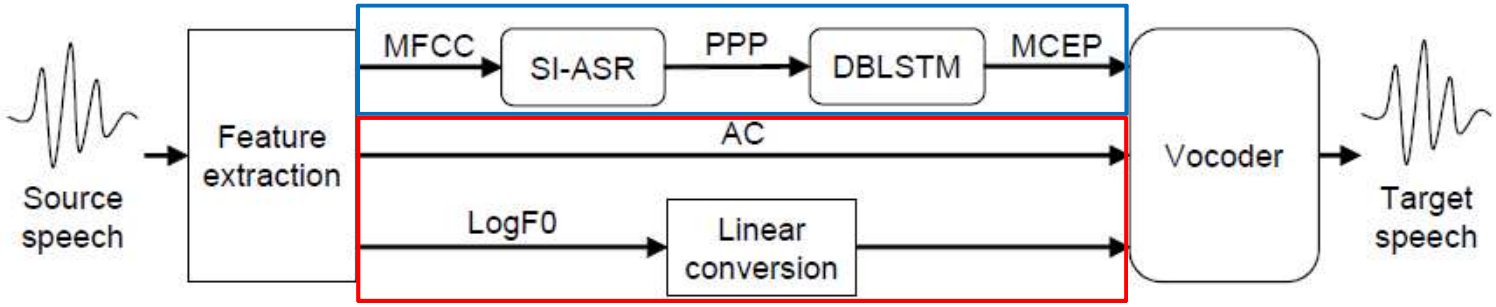
Feature extraction is a major factor of time delay

Experiments and Discussion

- Additional time measurement

Main proposal 1 – Parallel processing

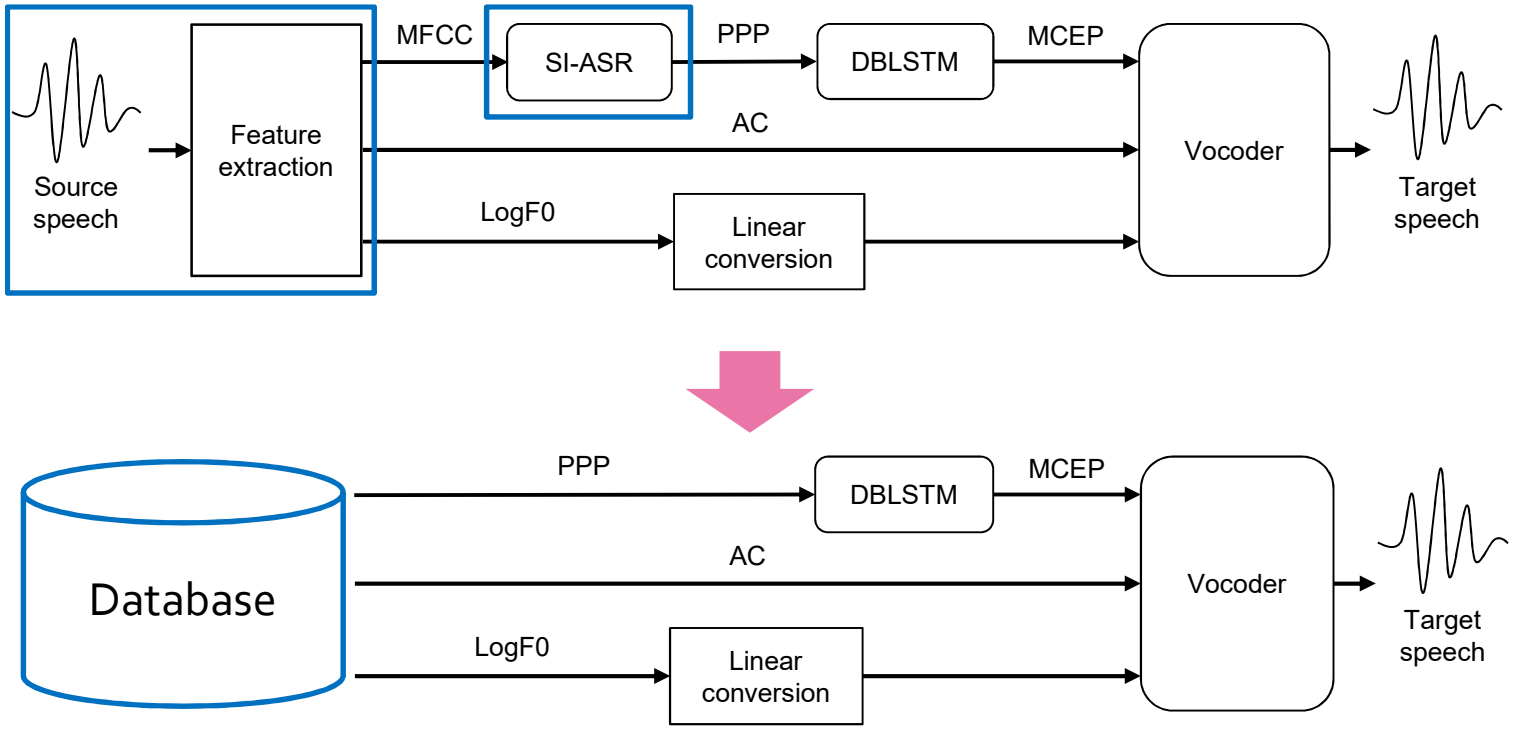
← SI-ASR and DBLSTM processes are independent of early process of vocoder



Experiments and Discussion

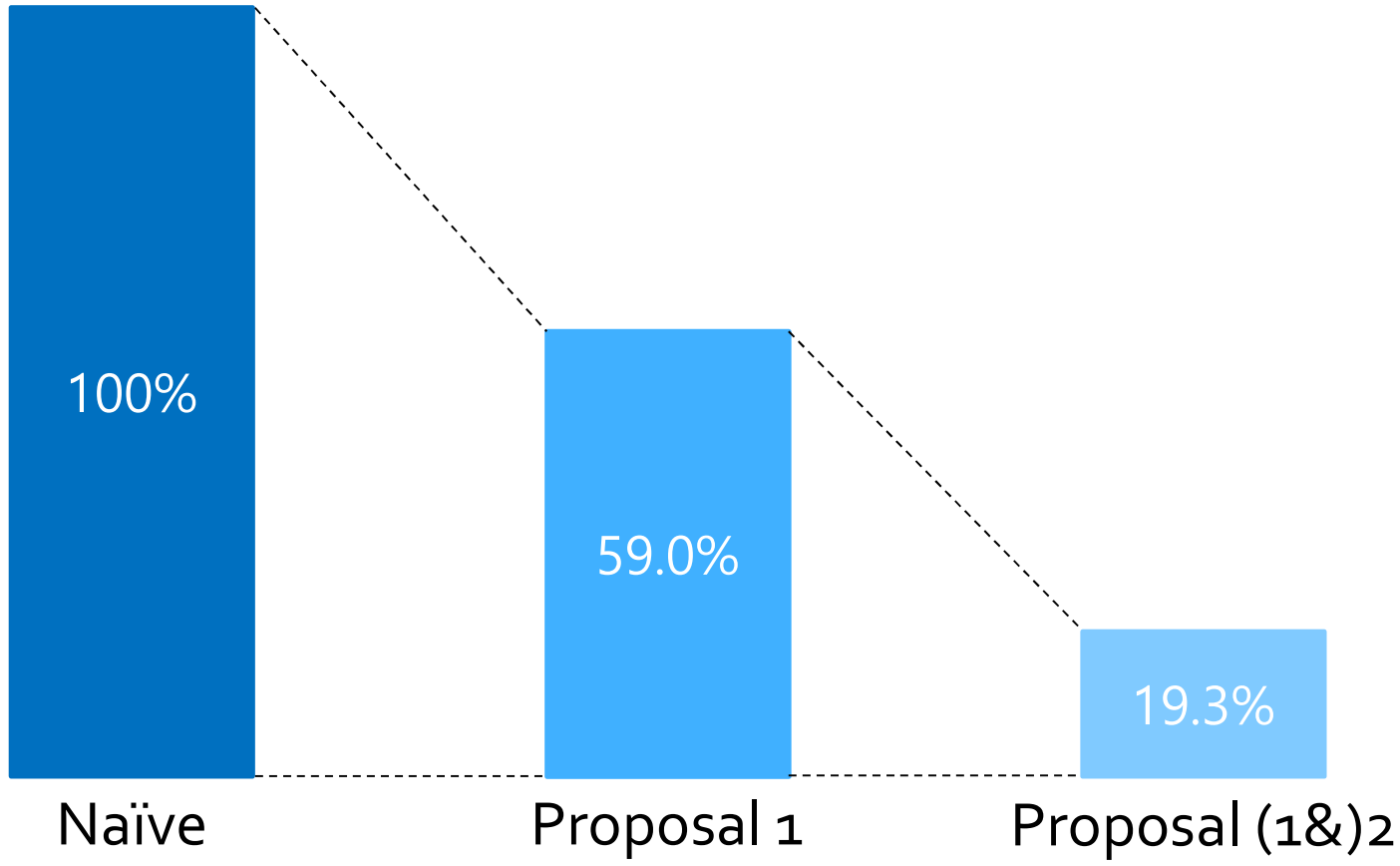
- Additional time measurement

Main proposal 2 – Extracting feature of Intu's voice in advance
← IBM Watson TTS follows unit selection method



Experiments and Discussion

- Additional time measurement



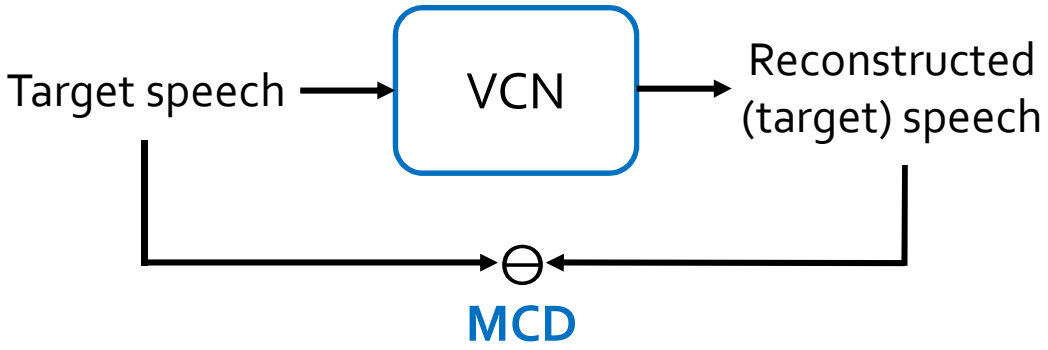
80.7% time reduction

Varying the size of target speech samples

- **Mel-cepstral distortion (MCD)**

  MCEP distance between original & reconstructed target speech [5]

$$MCD(dB) = \frac{10}{ln10}\sqrt{2\sum_{d=1}^{D}(c_d - c_d^{converted})^2}$$



Varying the size of target speech samples

- **Mel-cepstral distortion (MCD)**

  MCEP distance between original & reconstructed target speech [5]

$$MCD(dB) = \frac{10}{ln10}\sqrt{2\sum_{d=1}^{D}(c_d - c_d^{converted})^2}$$

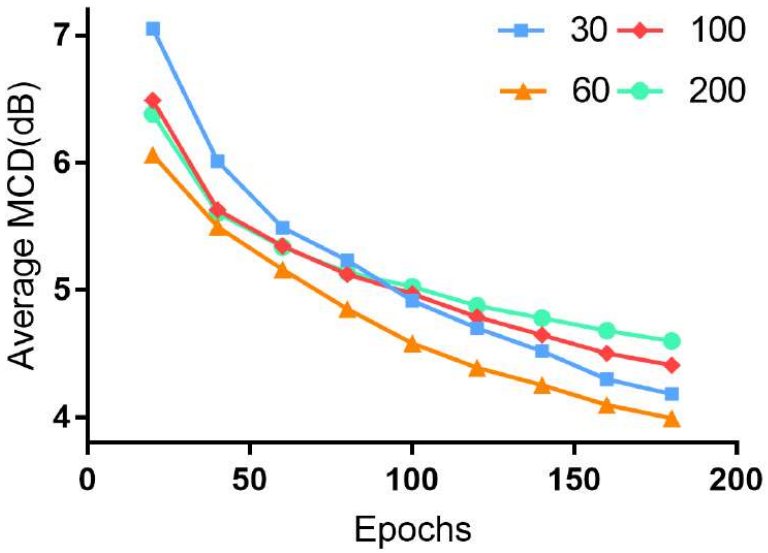
High MCD

Low MCD

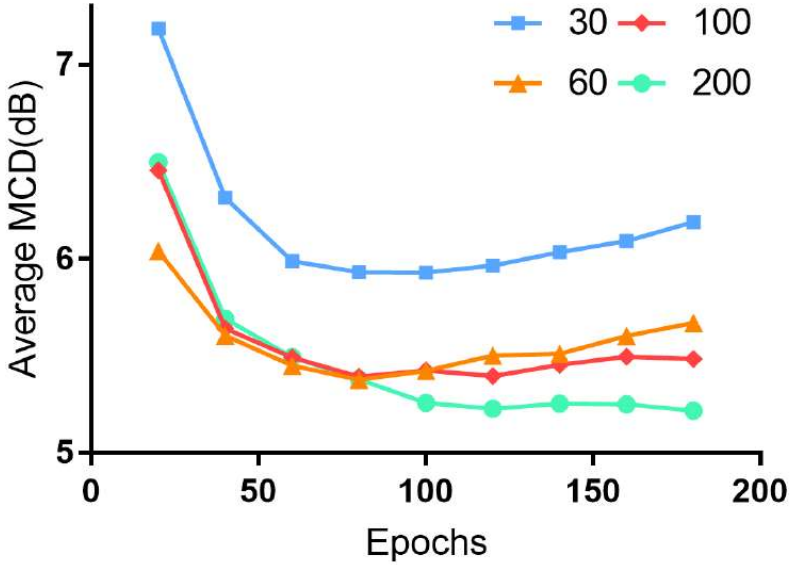
Experiments and Discussion

- Varying the size of target speech samples

MCD for training set



MCD for validation set



∴ 100+ of target speech samples avoid overfitting

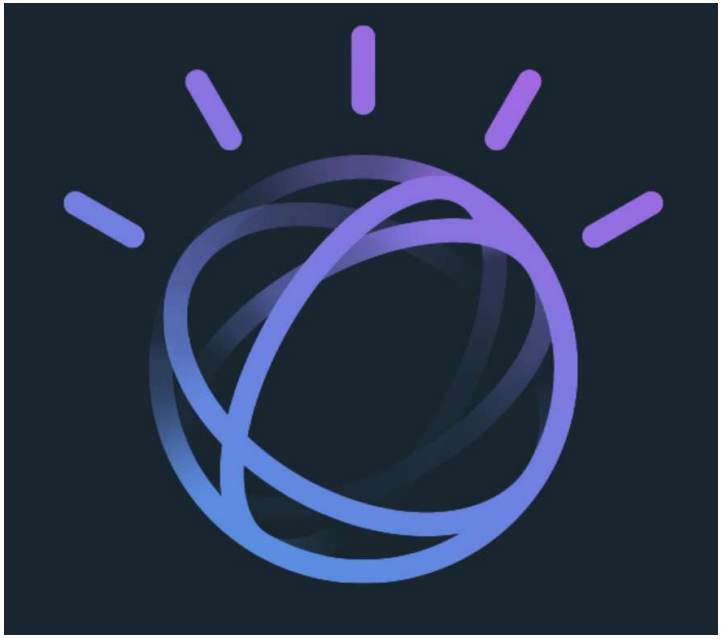
= 10~ min of target speech

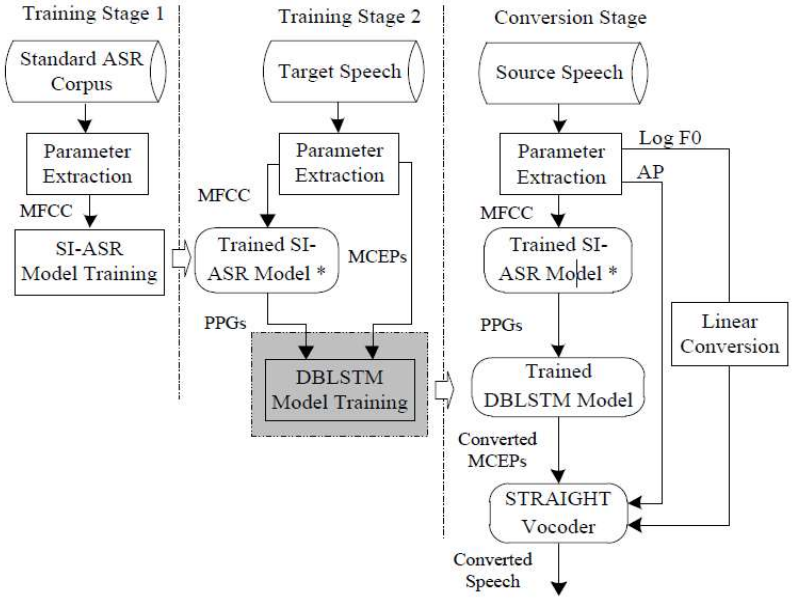
Outline

- Introduction
- Related Work
  - IBM Watson and Project Intu
  - Text-to-speech (TTS)
  - Voice conversion
- Model Description
  - Voice conversion network (VCN)
  - Intu
- Experiments and Discussion
- Conclusion

Conclusion

- TTS + VCN is suitable for voice customization service
- Parallel & pre-processing for optimization of inference time
- Our design requires user 10~ min of target speech





Acknowledgements

- Members of our laboratory

A picture with my advisor, his advisor (my academic grandpa) , and lab members
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(http://ailab.snu.ac.kr)

- Researchers in IBM Korea

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