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# Transformer-based text-to-speech with weighted forced attention

Takuma Okamoto<sup>1</sup>, Tomoki Toda<sup>2,1</sup>, Yoshinori Shiga<sup>1</sup> and Hisashi Kawai<sup>1</sup>

<sup>1</sup>National Institute of Information and Communications Technology (NICT), Japan <sup>2</sup>Nagoya University, Japan



## Outline

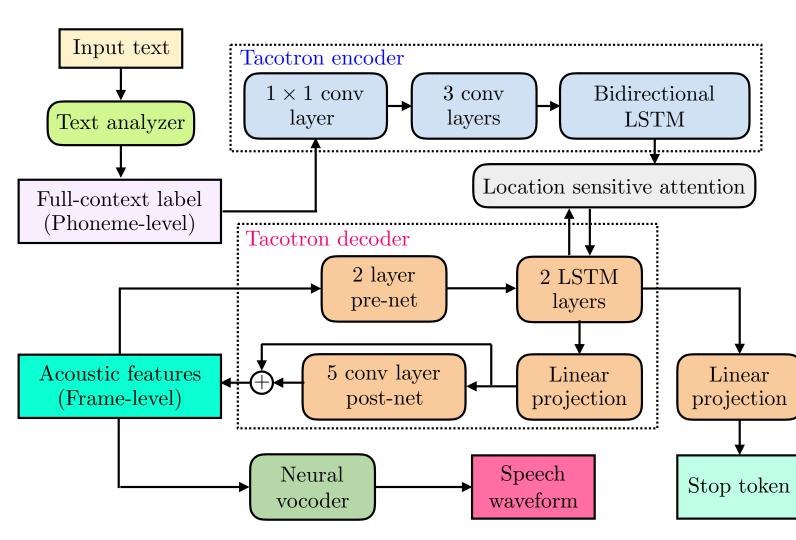
- Introduction
- Problems and purpose
- Proposed Transformer-based acoustic model with weighted forced attention
- FastSpeech without duration predictor
- Experiments
- Additional experiments (Not included in proceeding)
- Portable real-time neural TTS demo system on a laptop with a GPU
- Conclusions

## Introduction

- High-fidelity text-to-speech (TTS) systems
  - WaveNet outperformed conventional TTS systems in 2016 -> End-to-end neural TTS
- Tacotron 2 (+ WaveNet vocoder) J. Shen et al., ICASSP 2018
  - Text (English) -> [Tacotron 2] -> mel-spectrogram -> [WaveNet vocoder] -> speech waveform
  - In Jointly optimizing text analysis, duration and acoustic models with a single neural network
    - \*\* No text analysis, no phoneme alignment, and no fundamental frequency analysis

#### Realizing high-fidelity speech synthesis comparable to human speech!!

- Problem
  - \*\* NOT directly applied to pitch accent languages
- Tacotron 2 with full-context label input
  - Capable for pitch accent languages (e.g. Japanese)
    - \*\* Realizing real-time neural TTS with Tacotron 2 and WaveGlow
  - Crucial problem for actual implementations
    - **\*\*** Sometimes unstable in inference (skip or stop)

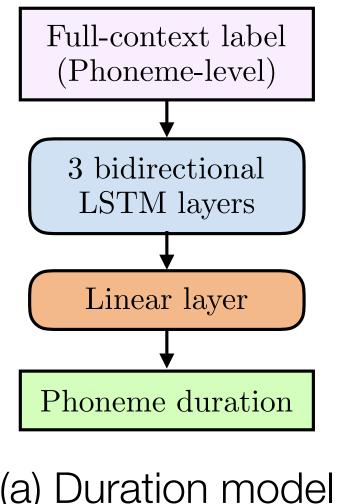


T. Okamoto et al., Interspeech 2019

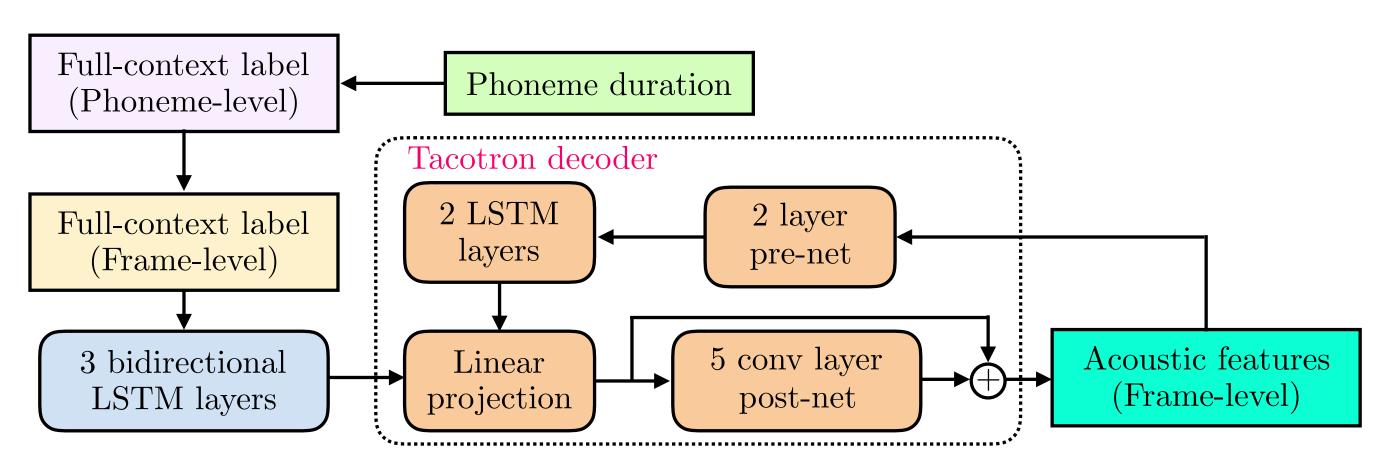
### Tacotron-based stable neural TTS model

T. Okamoto et al., ASRU 2019

- High-fidelity and stable acoustic model (AM)
- Conventional bidirectional LSTM-based duration model <- more stable compared with sequence-to-sequence models
  - \*\* Trained with HMM-based forced alignment
- Tacotron-based acoustic model with full-context label input
  - **\*\*** HMM-based forced alignment in training
  - \*\* Predicted phoneme durations are used in inference







(b) acoustic model: BLSTM+Taco2dec

High-fidelity, real-time and stable TTS can be realized with WaveGlow vocoder!!

## Problems and purpose

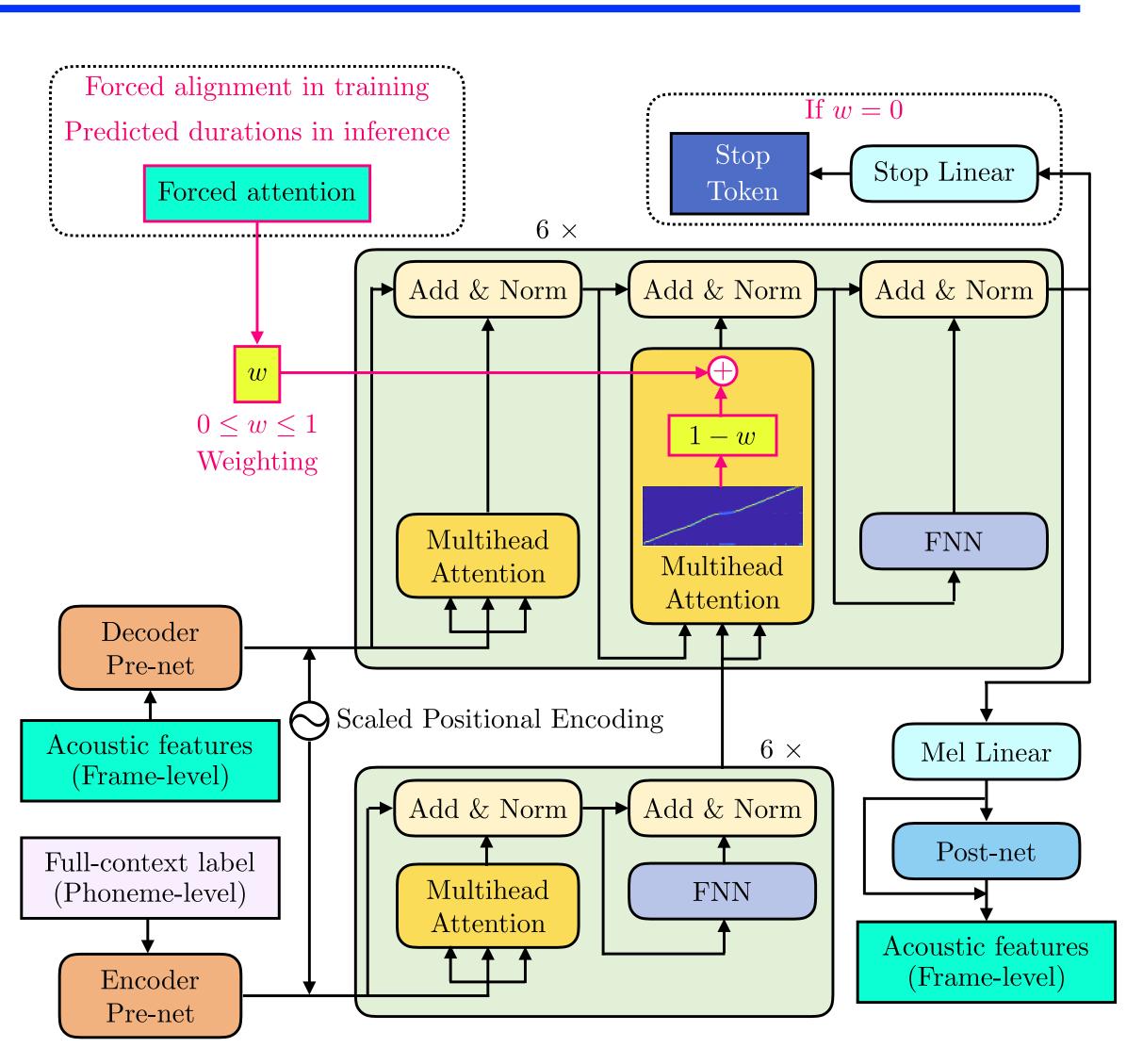
- Problem in RNN-based models (Tacotron 2 and BLSTM+Taco2dec)
  - Slower training period than CNN- and self-attention-based models (Transformer and FastSpeech)
- Problem in sequence-to-sequence models (Tacotron 2 and Transformer)
  - Sometimes unstable in inference (skip or stop)
    - \*\* Stable inference with phoneme durations (BLSTM+Taco2dec and FastSpeech)
- Problems in self-attention-based acoustic models (Transformer and FastSpeech)
  - Only phoneme input is investigated for English TTS
  - Teacher-student training (teacher Transformer) is required for FastSpeech
- Purpose of this study
  - Investigating Transformer- and FastSpeech-based AMs with full-context label input for pitch accent languages
  - Introducing HMM-based phoneme alignment to Transformer- and FastSpeech-based AMs
    - \*\* Stable inference for Transformer-based TTS
    - \*\* Removing teacher-student training and duration predictor in FastSpeech

# Transformer-based TTS with weighted forced attention

- Transformer-based TTS N. Li et al., AAAI 2019
  - Feedforward network and self-attention instead of RNN
    - \* Faster training than RNN-based models (e.g. Tacotron 2)
    - \*\* Only phoneme input is investigated for English TTS

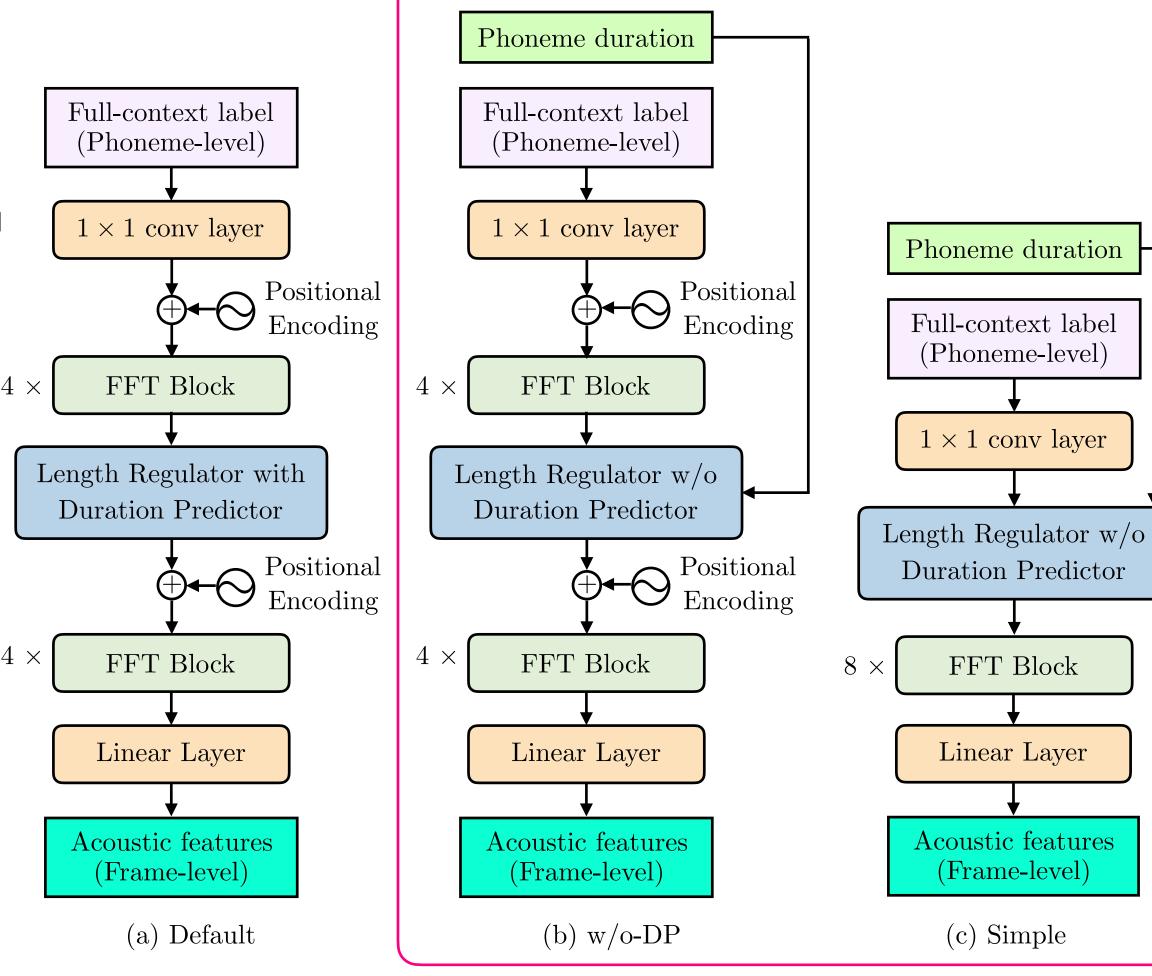
#### Proposed Transformer-based TTS

- Full-context label input for pitch accent languages
- Introducing wighted forced attention
  - **\*\*** HMM-based forced alignment in training
  - \*\* Duration predicted by conventional model in inference
  - \*\* Both multihued attention and predicted duration are simultaneously used with a weighting factor
  - **\*\*** For case of w=1, hidden features from encoder is too redundant (ASRU 2019) -> importance of weighting
  - \*\* Proposed AM can be trained without "stop token" loss



# FastSpeech without duration predictor

- FastSpeech Y. Ren et al., NeurlPS 2019
  - Feedforward Transformer without any recurrent connections
    - \*\* Not only fast training but also fast inference
  - Duration predictor trained from teacher Transformer's attention
    - \*\* Duration and acoustic models are jointly trained
  - Teacher-student training for improving synthesis accuracy
- FastSpeech without duration predictor
- Duration and acoustic models are <u>separately</u> trained
  - **\*\*** HMM-based forced alignment in training
  - \*\* Durations predicted by conventional model in inference
- FastSpeech with simple structure
  - Without encoder-decoder structure and positional encodings



(Phoneme-level)

 $1 \times 1$  conv layer

FFT Block

Linear Layer

(Frame-level)

(c) Simple

## Experimental conditions

- Speech corpus: Sampling frequency: 24 kHz
  - Japanese female corpus: about 22 h (test set: 80 utterances)

#### Acoustic models

- Input: full-context label vector (130 dim)
- Output acoustic feature: Mel-spectrograms (80 dim)
- Sequence-to-sequence models
  - \*\* Tacotron 2 (Interspeech 2019), Transformer (FNN: default), Transformer (Conv1D used in FastSpeech)
- Pipeline models with BLSTM-based duration model
  - **\*** BLSTM
  - **\*\*** BLSTM+Taco2dec(ASRU 2019)
  - \*\* Proposed Transformer with weighted forced attention (weightings are 0.2, 0.5, 0.7 and 1.0)
  - \*\* FastSpeech (default) with HMM-based forced alignment without teacher Transformer
  - **\*\*** Fastspeech without duration predictor
  - **\*\*** Fastspeech with simple structure
- Neural vocoder: WaveGlow with 512 channels

# Results of training period (TP) and real-time factor (RTF)

#### Evaluation condition

- Using an NVIDIA Tesla V100 GPU in inference
- Simple PyTorch implementation

#### Notations

TF: Transformer

WFA: Weighted forced attention

FS: FastSpeech

DP: duration predictor

Method	TP (days)	AM RTF	Total RTF
(A):Tacotron 2	24	0.063	0.13
(B):TF (FNN)	6	0.55	0.62
(C):TF (Conv1D)	6	0.55	0.62
(D):BLSTM	3	0.015	0.12
(E):BLSTM+Taco2dec	12	0.061	0.13
(F)-(I):TF-WFA	6	0.55	0.62
(J):FS (Default)	6	0.004	0.070
(K):FS (w/o-DP)	6	0.004	0.072
(L):FS (Simple)	6	0.004	0.072
Duration model	2	_	0.002
WaveGlow vocoder	30	_	0.066

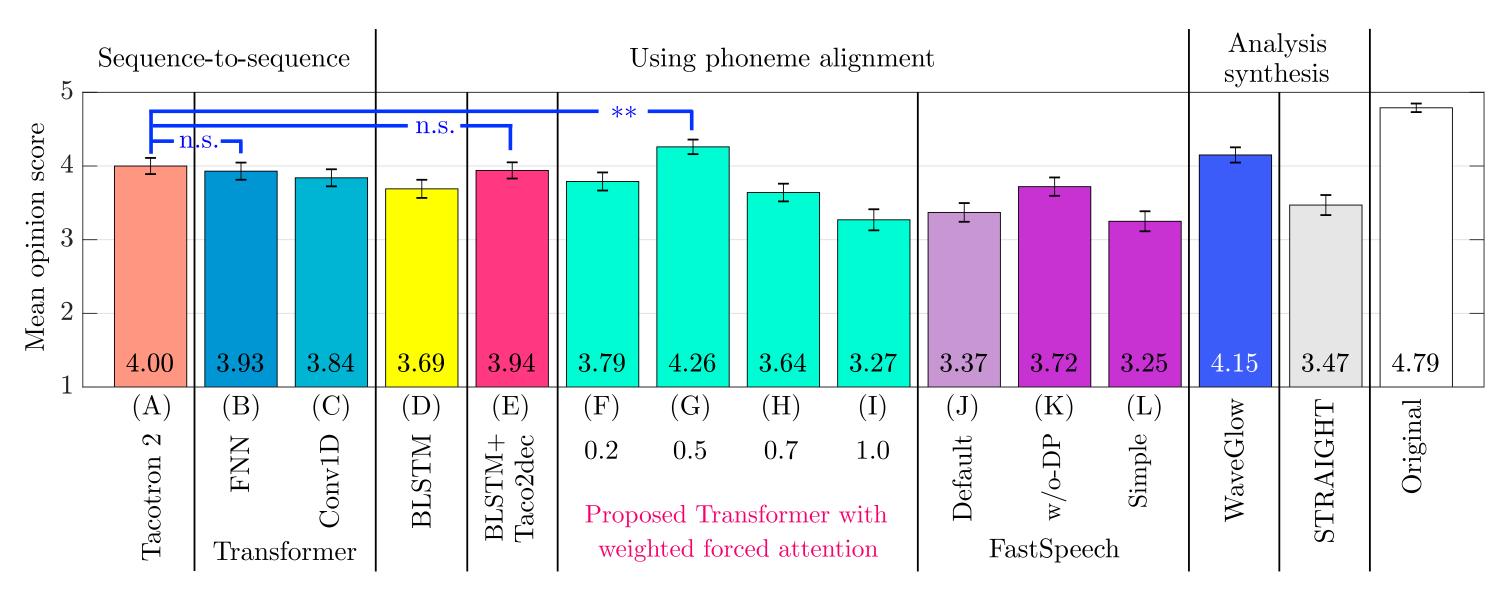
#### Results

- All models can realize real-time neural TTS with a GPU although Transformer-based model is not so fast
- Transformer and FastSpeech can realize faster training than Tacotron 2 and BLSTM+Taco2dec
- FastSpeech can realize fastest inference speed compared with other AMs

## MOS results

#### Subjective evaluation

- Listening subjects: 20 Japanese native speakers
- 15 conditions x 20 utterances (successfully synthesized by all models) = 300 sentences / a subject



#### Results

- Proposed Transformer-based AM with a weighting factor of 0.5 can significantly outperform other models
- FastSpeech without duration predictor can realize higher synthesis quality than that with duration predictor
- Proposed Transformer-based AMs with weighted forced attention included some unsuccessfully synthesized samples
  - \*\* Encoder and decoder attentions were not diagonal

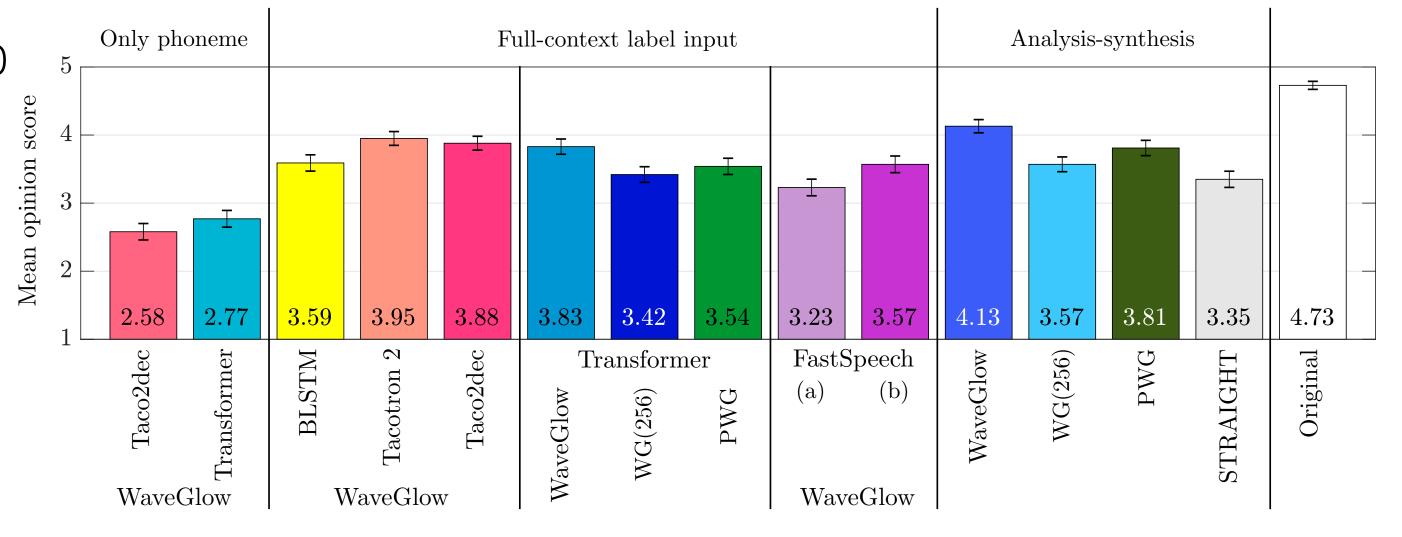
# Additional results (Not included in proceeding)

#### Additional experiments after submission of ICASSP 2020

- Only phoneme input condition
- Parallel WaveGAN (PWG): R. Yamamoto et al., ICASSP 2020
  - \*\* Training period: 2 days, Real-time factor: 0.031
- Small WaveGlow model with 256 channels
  - \*\* Training period: 12 days, Real-time factor: 0.030

#### Subjective evaluation

- Listening subjects: 15 Japanese native speakers
- $\blacksquare$  15 conditions x 20 utterances = 300 sentences



#### Results

- Parallel WaveGAN and small WaveGlow can realize faster training and inference than original WaveGlow
- WaveGlow with 512 channels can realize higher synthesis quality than other models
- Importance of full-context label input for Japanese TTS

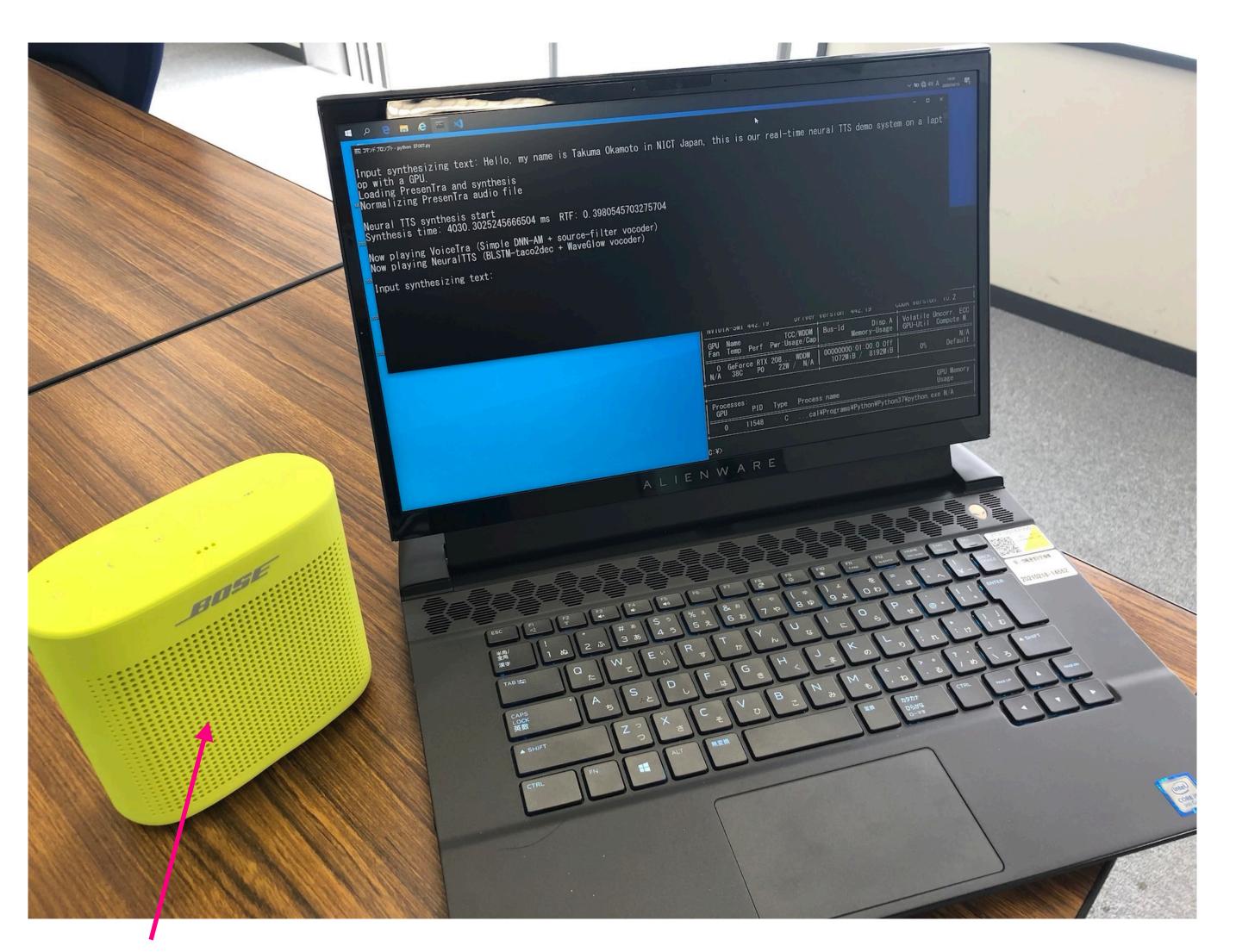
## Portable real-time neural TTS demo system

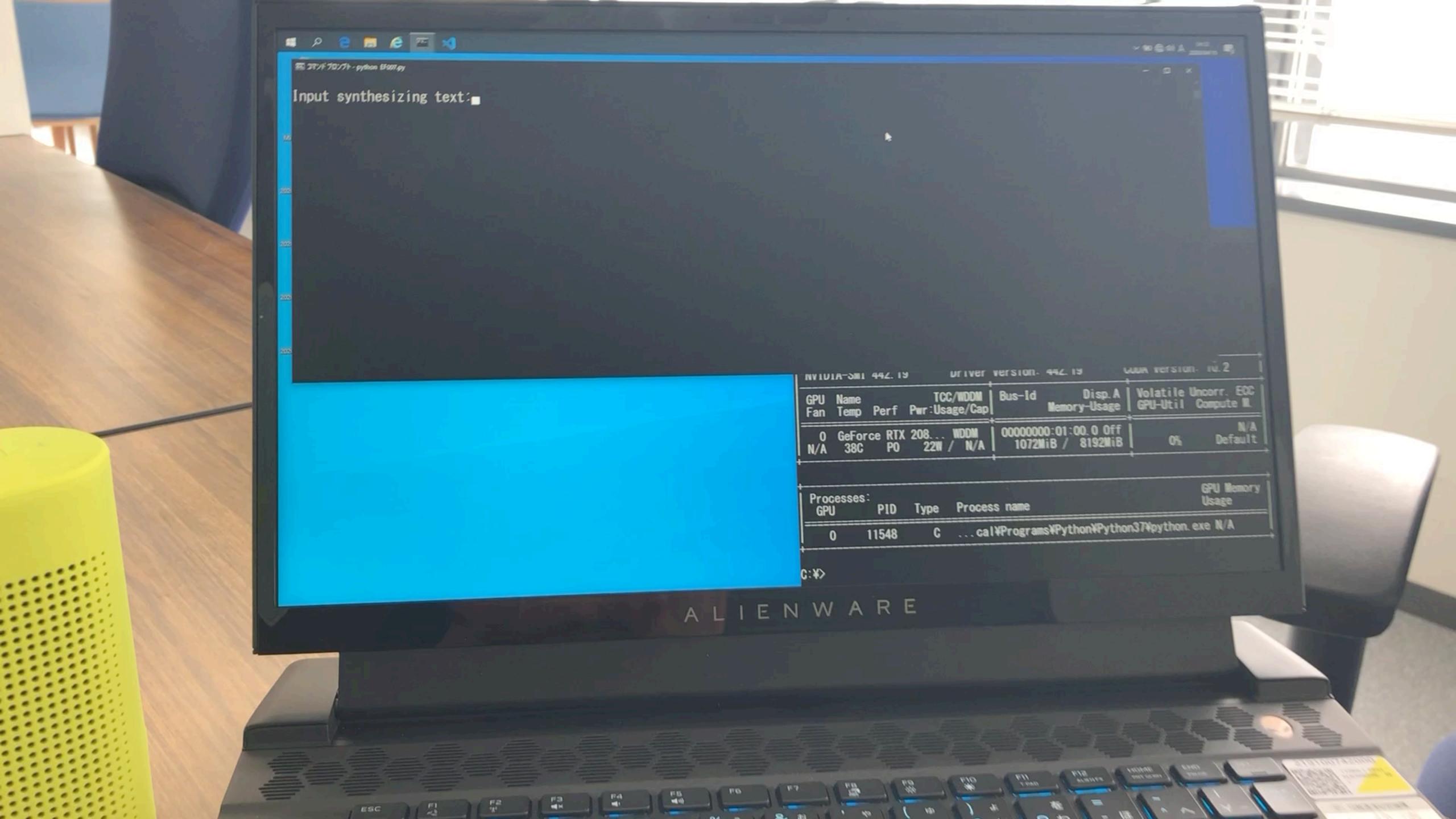
#### Laptop: DELL ALIENWARE M15

- GPU: NVIDIA GeForce RTX 2080
- CPU: Intel Core i7-9750H 6 cores
- Memory: 16 GB DDR4 2,666 MHz
- 512 GB PCle M.2 SSD
- Windows 10 Professional

#### Real-time neural TTS demo system

- Simple PyTorch implementation
- Acoustic model: BLSTM-Taco2dec
- Neural vocoder: WaveGlow
- Neural TTS models
  - \* 4 Japanese speakers (female and male)
  - **\*\*** 2 English speakers (female and male)
- Total real-time factor: about 0.4





## Conclusions

#### Transformer-based TTS with weighted forced attention

- Transformer- and FastSpeech-based AMs with full-context label input can also be successfully trained
- Proposed Transformer-based AM with a weighting factor of 0.5 can significantly improve synthesis accuracy
- FastSpeech without duration predictor can realize higher synthesis quality than that with duration predictor
- Proposed Transformer-based AMs with weighted forced attention cannot improve synthesis stability

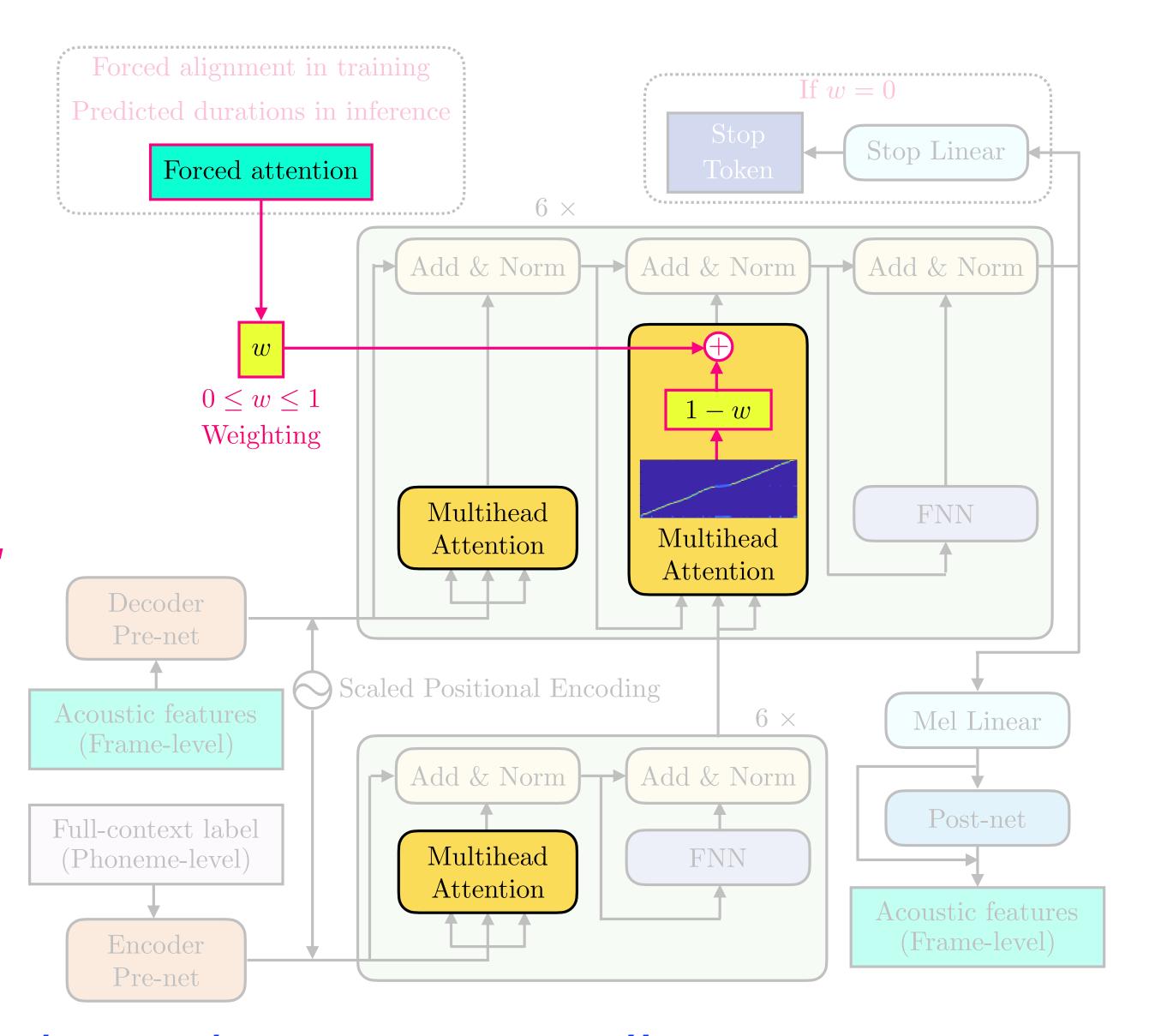
#### Future work

- Improving stability of transformer-based TTS for actual implementations by introducing trainable weighting factors
- Introducing weighted forced attention to Tacotron 2
- Introducing teacher-student training in FastSpeech-based AMs for higher synthesis accuracy

#### Demo samples

Synthesized speech samples used in experiments are available https://ast-astrec.nict.go.jp/demo\_samples/icassp\_2020\_okamoto/index.html

# Thank you for your



If you have any questions, please contact us!! okamoto@nict.go.jp