

# The NITech text-to-speech system for the Blizzard Challenge 2018

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# Background

## ○ Text-to-speech (TTS) systems

- ◆ TTS systems are used in various applications
- ◆ Demand for TTS systems is increasing
  - *High-quality, various speaking styles, various languages, etc.*
- ◆ Success by introducing deep learning
  - *DNN, LSTM, WaveNet, Deep Voice, Char2Wav, Tacotron, etc.*

## ○ Evaluations of TTS systems

- ◆ Comparisons are difficult when the training corpus, task, and listening test are different
- ◆ Blizzard Challenge [Black et al. '05]
  - *In order to better understand and compare research techniques in constructing corpus-based TTS systems with the same data*

## ○ NITech TTS system for the Blizzard Challenge

- ◆ NITech have been submitting a statistical speech synthesis system to the Blizzard Challenge since 2005

# Blizzard Challenge 2015-2018

## ○ Task

- ◆ Construct a TTS system from children's audiobooks that is suitable for reading audiobooks to children

## ○ Data

- ◆ Children's audiobooks were recorded by one female speaker
  - 2015 (*pilot task year*): 2 hours
  - 2016: 5 hours
  - 2017, 2018: 7 hours
- ◆ Mismatches between speech data and text
  - *Misreading, onomatopoeia, etc.*
- ◆ Speech data includes various speaking styles
  - *Emotions, characters, singing voices, etc.*



"I'm king of the jungle," roared Lion.

"I'm going to eat you all up."









"No!" cried the jungle animals.

Character1

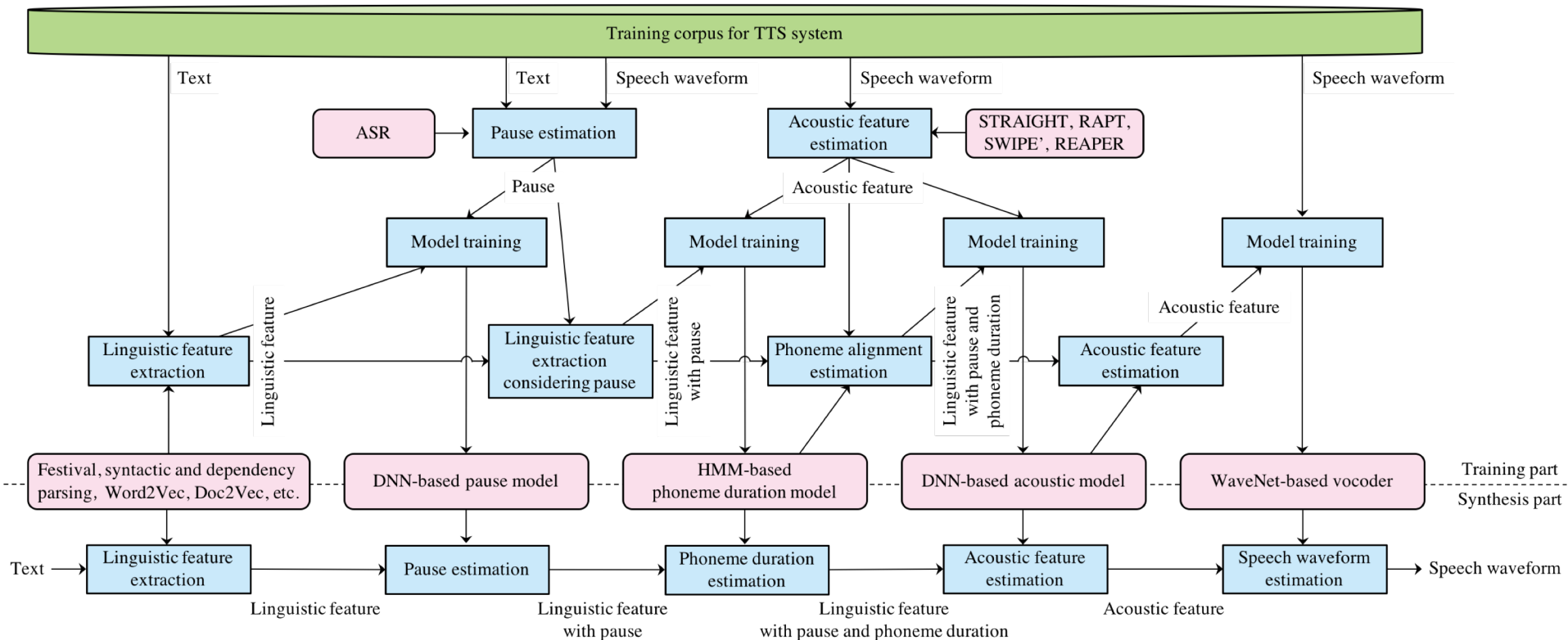
Character2

Descriptive part

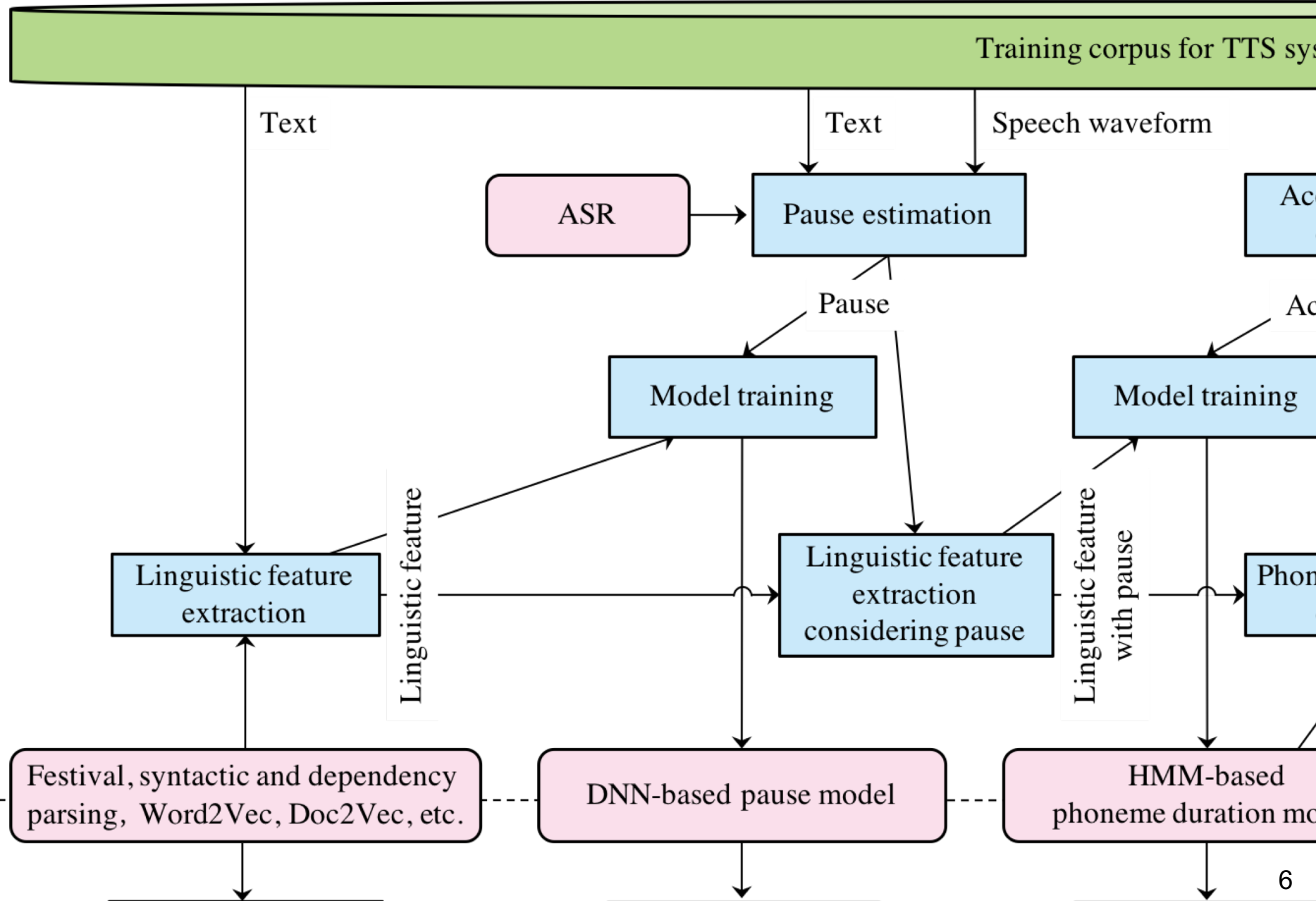
# NItech 2015-2018 TTS systems

- **NItech 2015 TTS system**  
  - ◆ Pruning of training data based on ASR
  - ◆ Introduction of linguistic features based on quotation marks
- **NItech 2016 TTS system**  
  - ◆ Automatic construction of training corpus based on ASR
  - ◆ Introduction of linguistic features based on syntactic parsing
  - ◆ Introduction of DNN acoustic model considering GV trajectory
- **NItech 2017 TTS system**  
  - ◆ Introduction of linguistic features which can predict and reproduce speaking style from text
  - ◆ Introduction of MDN acoustic model considering GV trajectory
- **NItech 2018 TTS system**  
  - ◆ Introduce pause insertion model
  - ◆ Introduce WaveNet vocoder

# NITech 2018 TTS system



# NI Tech 2018 TTS system



# Pause insertion model

## ○ Pause insertion

- ◆ Pause is used as one of emotional expressions

⇒ Introduce pause insertion model to reproduce pause insertion style of training corpus

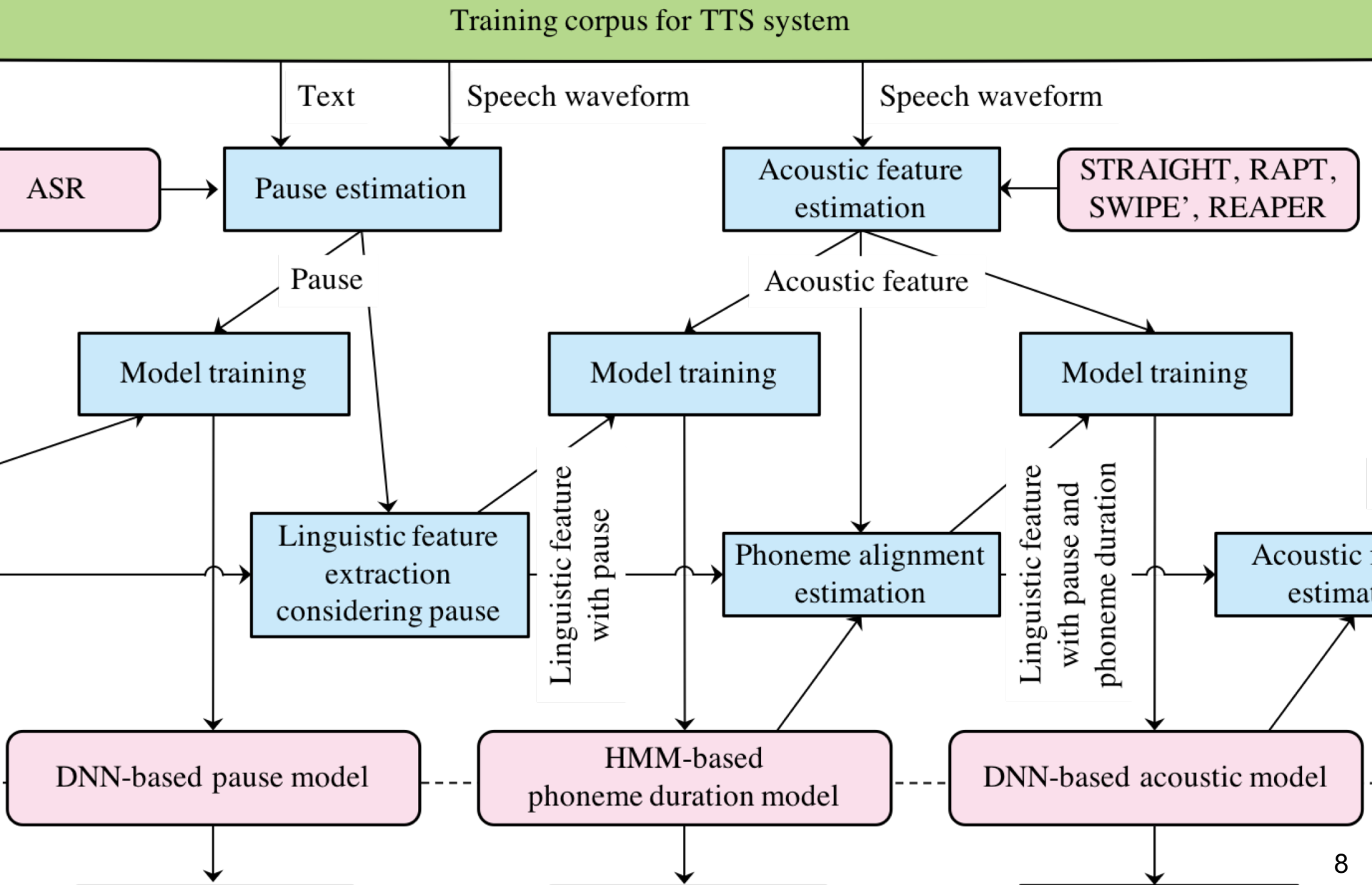
## ○ Pause estimation of training corpus

- ◆ Phoneme alignment estimation including short pause at all word boundaries
- ◆ Short pause model (HMM with state skip transition)
- ◆ Duration of estimated short pause is equal to or greater than threshold ⇒ word boundary contains a pause

## ○ Pause insertion model

- ◆ Bi-directional gated recurrent unit (GRU)
- ◆ Input: linguistic features of word- and sentence-level
- ◆ Output: whether or not a pause is inserted after the word (0 or 1)

# NITech 2018 TTS system

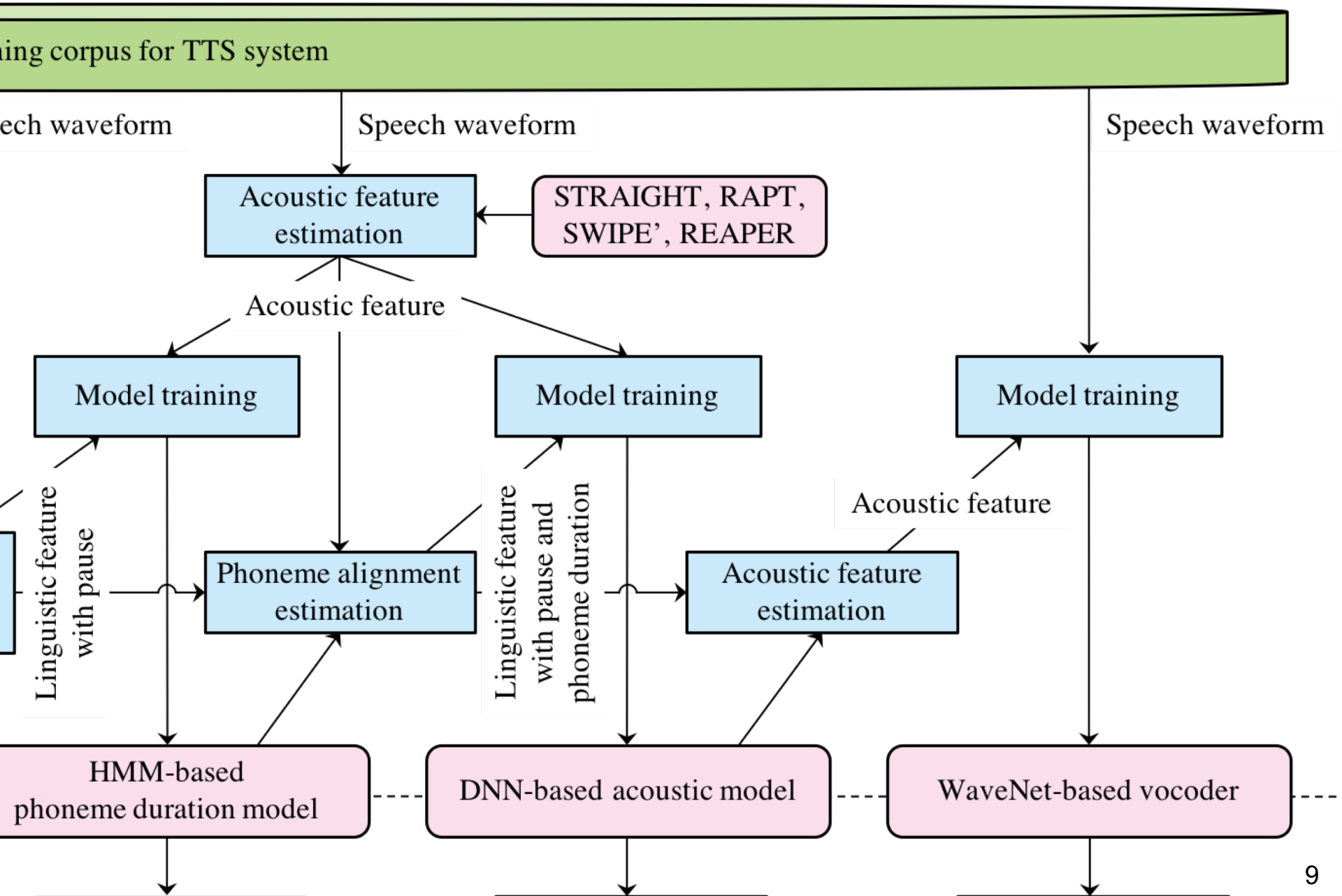




The diagram illustrates the architecture of a TTS system, showing the flow from input waveforms to the final vocoder output. The process is divided into three main paths, all originating from a 'Training corpus for TTS system' at the top.

- Left Path (HMM-based):** A 'Tech waveform' is processed through 'Acoustic feature estimation' (utilizing 'STRAIGHT, RAPT, SWIPE', REAPER') to produce 'Acoustic feature'. This feature is used for 'Model training' and 'Phoneme alignment estimation'. 'Linguistic feature with pause' is also input to 'Phoneme alignment estimation'. The output of 'Phoneme alignment estimation' is used for 'Model training' and the 'HMM-based phoneme duration model'.
- Middle Path (DNN-based):** A 'Speech waveform' is processed through 'Acoustic feature estimation' to produce 'Acoustic feature'. This feature is used for 'Model training' and 'Phoneme alignment estimation'. 'Linguistic feature with pause and phoneme duration' is also input to 'Phoneme alignment estimation'. The output of 'Phoneme alignment estimation' is used for 'Model training' and the 'DNN-based acoustic model'.
- Right Path (WaveNet-based):** A 'Speech waveform' is processed through 'Acoustic feature estimation' to produce 'Acoustic feature'. This feature is used for 'Model training' and the 'WaveNet-based vocoder'.

The final outputs of the three paths are connected by dashed lines, indicating a shared or sequential relationship between the 'HMM-based phoneme duration model', the 'DNN-based acoustic model', and the 'WaveNet-based vocoder'.



# WaveNet-based vocoder

- **Frame-level vocoder**

- ◆ Vocoder introduce degradation in speech quality  
⇒ **Introduce neural vocoder**

- **WaveNet vocoder** [van den Oord et al.; '16], [Tamamori et al.; '17]

- ◆ **Directly modeling and generation speech waveform**
- ◆ Modeling speech waveform as classification problem
- ◆ **Quantization scheme introduces flat white noise**  
⇒ Introduce noise shaping quantization

[Yoshimura et al.; '18]

- **Mel-cepstrum-based quantization noise shaping**

- ◆ **Quantization noise considering human auditory**
- ◆ Apply mel-cepstrum-based prefilter to speech signals

[Tokuda et al.; '94]

Realize high-quality speech waveform generation

# Experimental conditions (1/3)

## ○ Conditions of training corpus construction

Provided data	1258 pages
Acoustic features	12 dim. MFCC + $\Delta$ + $\Delta\Delta$
Acoustic model	3 state left-to-right tri-phone GMM-HMM
Language model	Tri-gram
Training corpus for TTS	924 pages

## ○ Conditions of pause insertion model

Input features	251 dim. linguistic features
Structure of DNN	Bi-directional gated recurrent unit, 3 hidden layers, 128 units, ReLU
Training algorithm	Adam, dropout rate 20%

# Experimental conditions (2/3)

## ○ Conditions of phoneme duration model

Sampling rate	32 kHz
Acoustic features	64 dim. STRAIGHT mel-cepstrum, log F0, 32 dim. mel-cepstrum aperiodicity measure + $\Delta$ + $\Delta\Delta$
Number of questions	925 questions
Structure of HMM	5 state left-to-right MSD-HSMM

## ○ Conditions of acoustic model

Sampling rate	32 kHz
Acoustic features	64 dim. STRAIGHT mel-cepstrum, log F0 V/UV info., 32 dim. mel-cepstrum aperiodicity measure
Linguistic features	1685 dim.
Structure of DNN	Single-mixture density network, 3 hidden layers, 8000 units, sigmoid
Training algorithm	SGD, dropout rate 60%, Trajectory training considering GV

# Experimental conditions (3/3)

## ○ Conditions of WaveNet vocoder

Sampling rate	32 kHz
Quantization	8 bit $\mu$ -law
Noise shaping parameters	$\gamma = 0.1$ , $\beta = 0.1$
Structure of WaveNet	Dilation: [1, 2, 4, ..., 512] 3 stacks Dilation, residual, skip: 256
Condition features of WaveNet	98 dim. acoustic features
Training algorithm	Adam

# Demo

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# Evaluation results of sentence domain

## Naturalness

MOS	ID
4.8	A
4.0	K
3.7	J
3.5	I
3.0	L, M
2.9	B
2.8	D
	⋮

## Similarity

MOS	ID
4.5	A
3.9	K
3.6	J
3.5	I
3.4	L
3.2	B
3.0	M
	⋮

## Intelligibility

WER	ID
11	I
14	E, O
15	D, G
16	K
17	N
18	J
20	F
	⋮

A: Natural speech

B, C, D, E: Benchmark TTS systems

I: NITech TTS system

Red line: Significant difference between NITech and other systems

# Evaluation results of page domain

## Overall impression

MOS	ID
48	A
38	K
34	J, I
29	B
28	L
	⋮

## Pleasantness

MOS	ID
48	A
37	K
33	J, I
28	L, B
26	M
	⋮

## Speech pause

MOS	ID
48	A
36	K, J
32	I
31	D, G
30	E
	⋮

## Stress

MOS	ID
48	A
36	K
35	J
33	I
30	D, G
	⋮

## Intonation

MOS	ID
48	A
37	K
35	J
33	I
28	D
	⋮

## Emotion

MOS	ID
48	A
38	K
35	J, I
31	B
30	M
	⋮

## Listening effort







MOS	ID
49	A
37	K
34	J
33	I
28	D
	⋮



# Comparison of NITech 2017 and 2018

## ○ Introduction of WaveNet vocoder

- ◆ Improved naturalness and speaker similarity
- ◆ Sometimes ambiguous pronunciation
  - *Multiple codecs and noise made WaveNet training difficult*
- ◆ Reduced reproducibility of speaking styles
  - *Training data is insufficient to reproduce various speaking styles*

2017	2018
	
	
	

# Conclusion

## ○ NITech TTS system for the Blizzard Challenge 2018

- ◆ Introduce pause insertion model
- ◆ Introduce WaveNet vocoder
- ◆ Large-scale subjective listening tests
  - *Synthesized highly natural, similar, and intelligible speech*
- ◆ Comparison of NITech 2017 and 2018 TTS systems
  - *Improved naturalness and speaker similarity*
  - *Insufficient accuracy of WaveNet vocoder*

## ○ Future work

- ◆ Generate expressive synthesized speech in neural vocoder
- ◆ Introduce end-to-end approach