Deep Learning for Audio

Lecture 5

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Outline

1. Text-to-speech
2. Attention ideas in TTS
3. SOTA TTS models

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Text-to-speech (TTS)

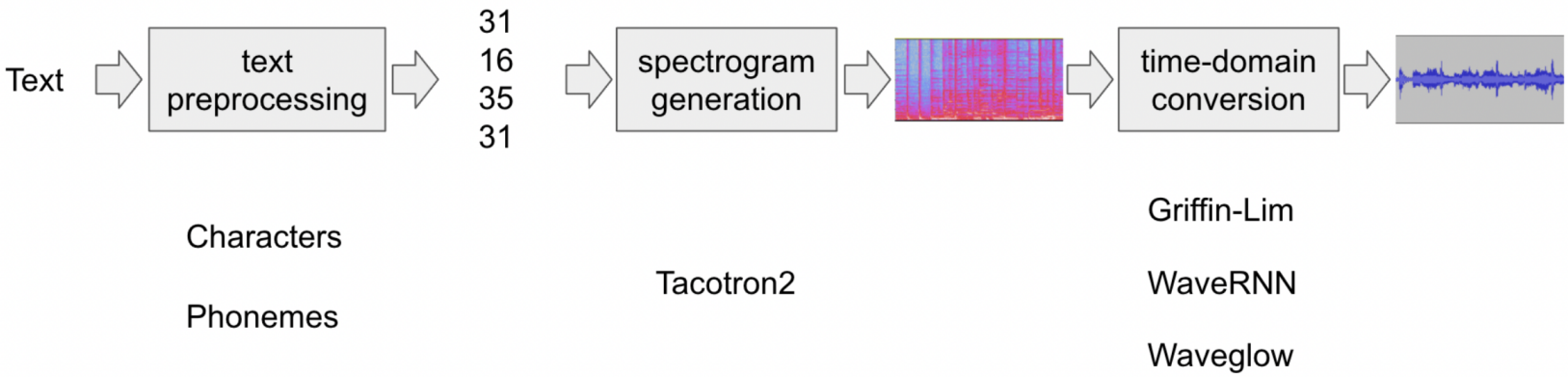

Figure: Base pipeline of Text-to-speech task

Datasets: LJSpeech, LibriTTS, CommonVoice, OpenTTS (Ru)

TTS: quality

- Quality: Subjective perception
- Overall impression, Intelligibility, Similarity, Naturalness, Pleasantness, Intonation and pauses, Emotions, Listening effort
- Mean Opinion Score (MOS): Crowdsourcing by Yandex Toloka/Amazon

$$\text{MOS} = \frac{\sum_{n=1}^{N} \mathcal{R}_n}{N}$$

Rating	Quality	Distortion
5	Excellent	Imperceptible
4	Good	Just perceptible, but not annoying
3	Fair	Perceptible and slightly annoying
2	Poor	Annoying, but not objectionable
1	Bad	Very annoying and objectionable

- Side-by-Side audio comparison (evaluate small improvements)

Outline

Tacotron 2

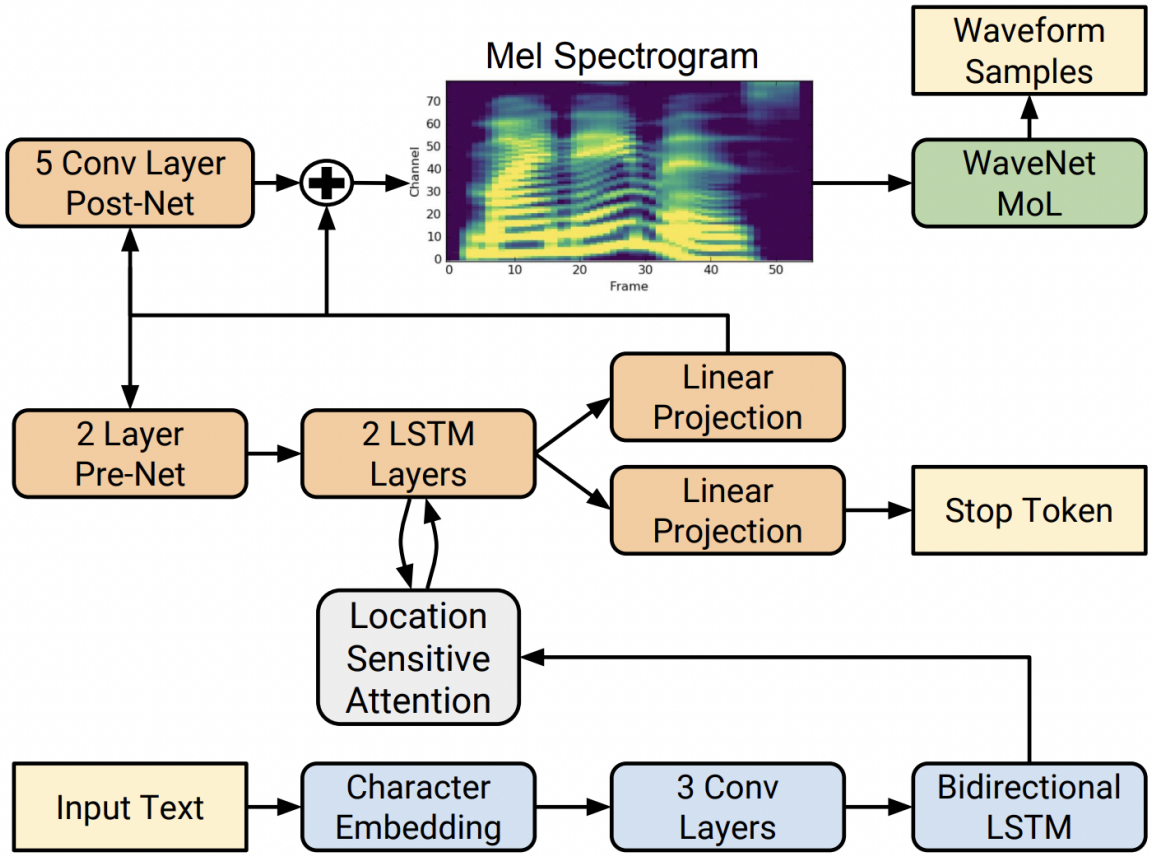

Figure: Recurrent seq-to-seq feature prediction network with attention that maps character embeddings to spectrograms, followed by a modified WaveNet to synthesize time-domain waveforms

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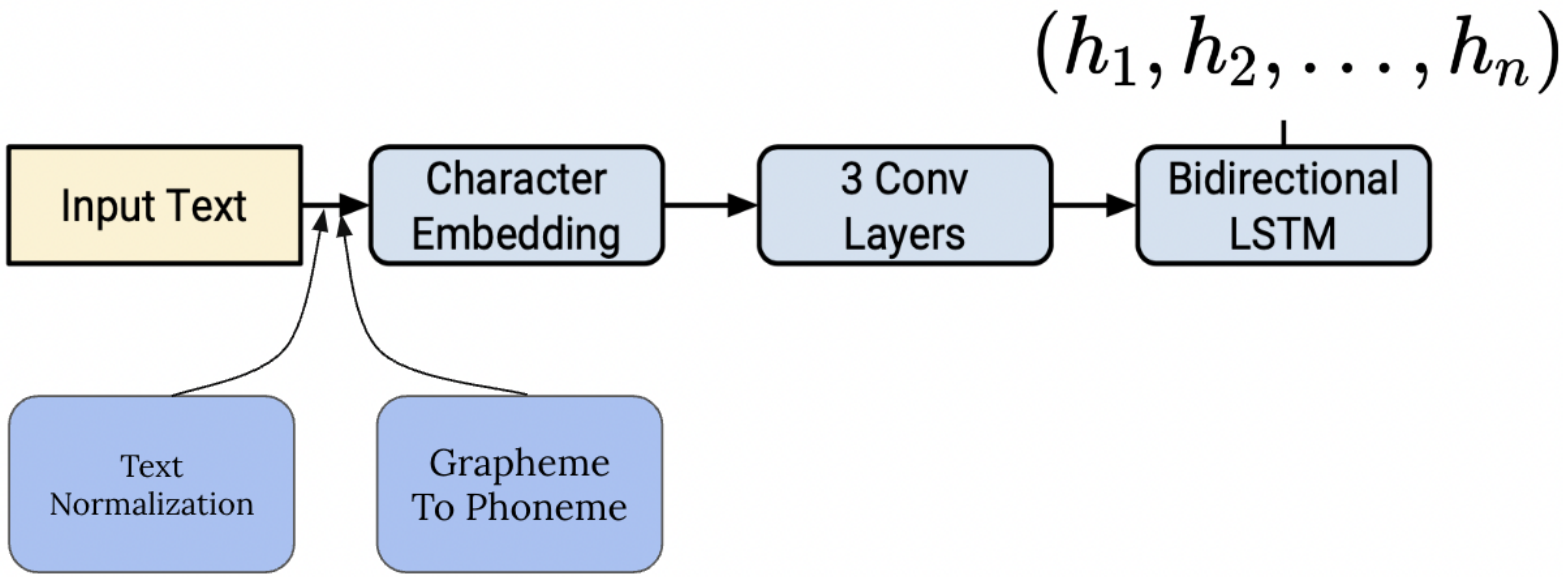
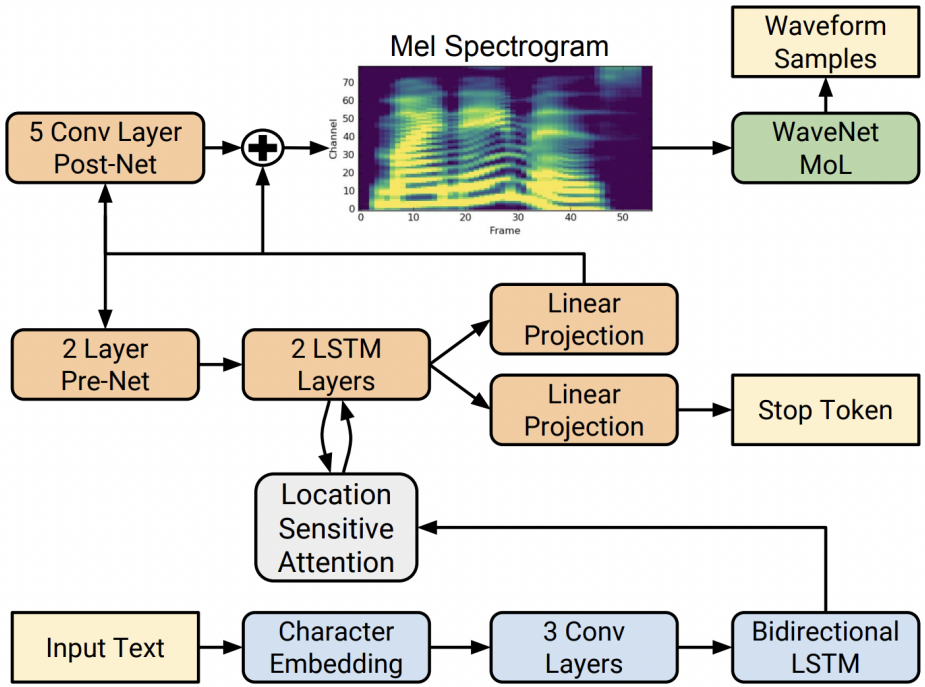
Shen et al., Natural TTS Synthesis by Conditioning Wavenet on MEL Spectrogram Predictions, 2018 IEEE ICASSP

Tacotron 2: text Encoder



Tacotron 2



$$\mathcal{L} = \mathcal{L}_{\text{pre}} + \mathcal{L}_{\text{post}} + \text{StopToken}$$

$$\mathcal{L}_{\text{pre}} = \text{MSE}(x, \hat{x}_{\text{pre}})$$

$$\mathcal{L}_{\text{post}} = \text{MSE}(x, \hat{x}_{\text{post}})$$

$$\text{StopToken} = \text{CE}(a, \mathcal{I}[h = \text{Stop}])$$

Guided Attention

- Idea: text position n progresses nearly linearly to the time t:

$$n \sim at, \;\; a \sim N/T$$

- Add loss $\mathcal{L}_{\text{att}}(A) = \mathbb{E}_{nt}[A_{nt} W_{nt}]$, where $W_{nt} = 1 - \exp\{-(n/N - t/T)^2/2g^2\}, \quad g = 0.2, \quad A \in \mathbb{R}^{N \times T}$

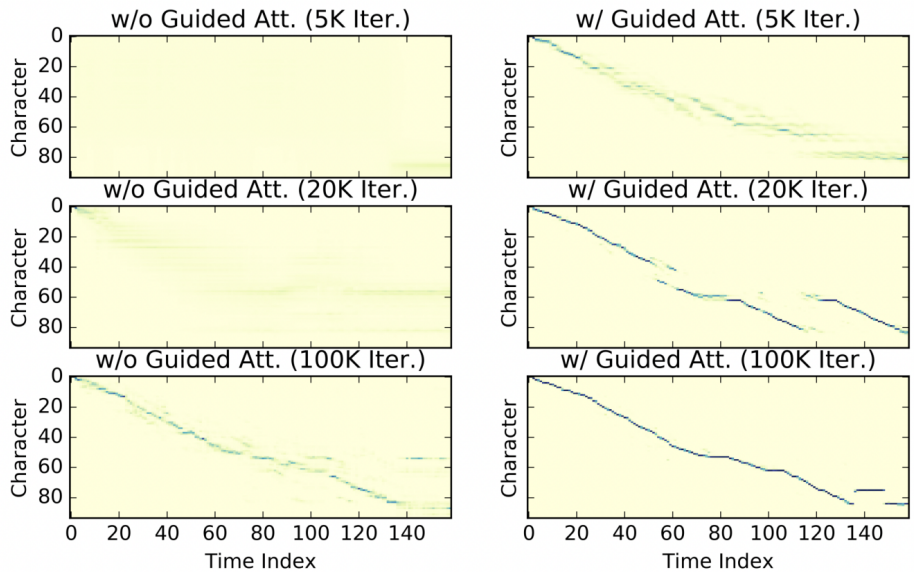


Figure: Comparison of the attention matrix A, trained with (Right) and without (Left) the guided attention loss

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Tachibanaet al., Efficiently Trainable Text-to-Speech System Based on Deep Convolutional Networks with Guided Attention, 2018 IEEE ICASSP

Monotonic Attention

For $j = t_{i-1}, t_{i-1}+1, t_{i-1}+2, \ldots$:

$$e_{i,j} = a(s_{i-1}, h_j)$$
$$p_{i,j} = \sigma(e_{i,j})$$
$$z_{i,j} \sim \text{Bernoulli}(p_{i,j})$$

where $a(\cdot)$ – learnable deterministic "energy function", $\sigma(\cdot)$ – logistic sigmoid function

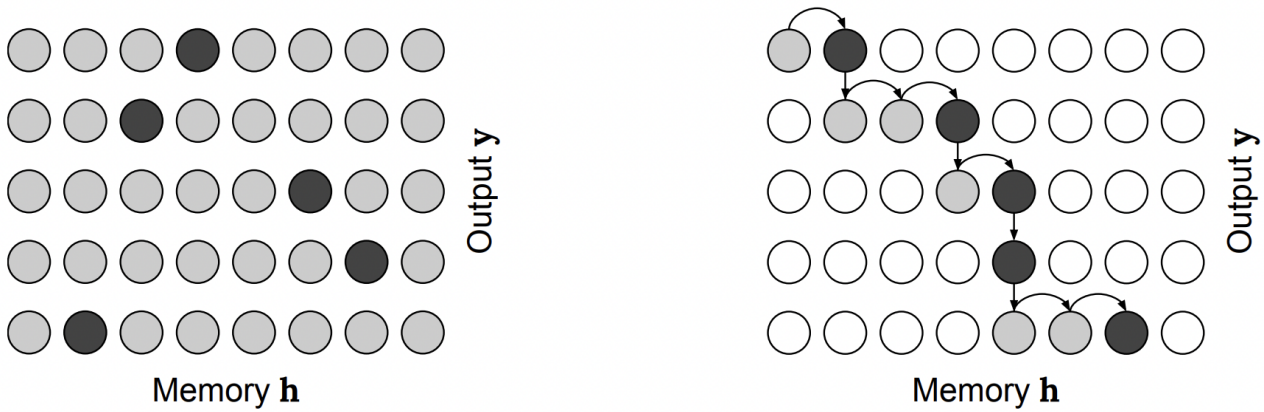

Figure: Left: schematic of the stochastic process underlying softmax-based attention decoders. Right: monotonic stochastic decoding process.

Raffel et al., Online and Linear-Time Attention by Enforcing Monotonic Alignments, Algorithms, A.G., 2017

Global Style Token (GST)

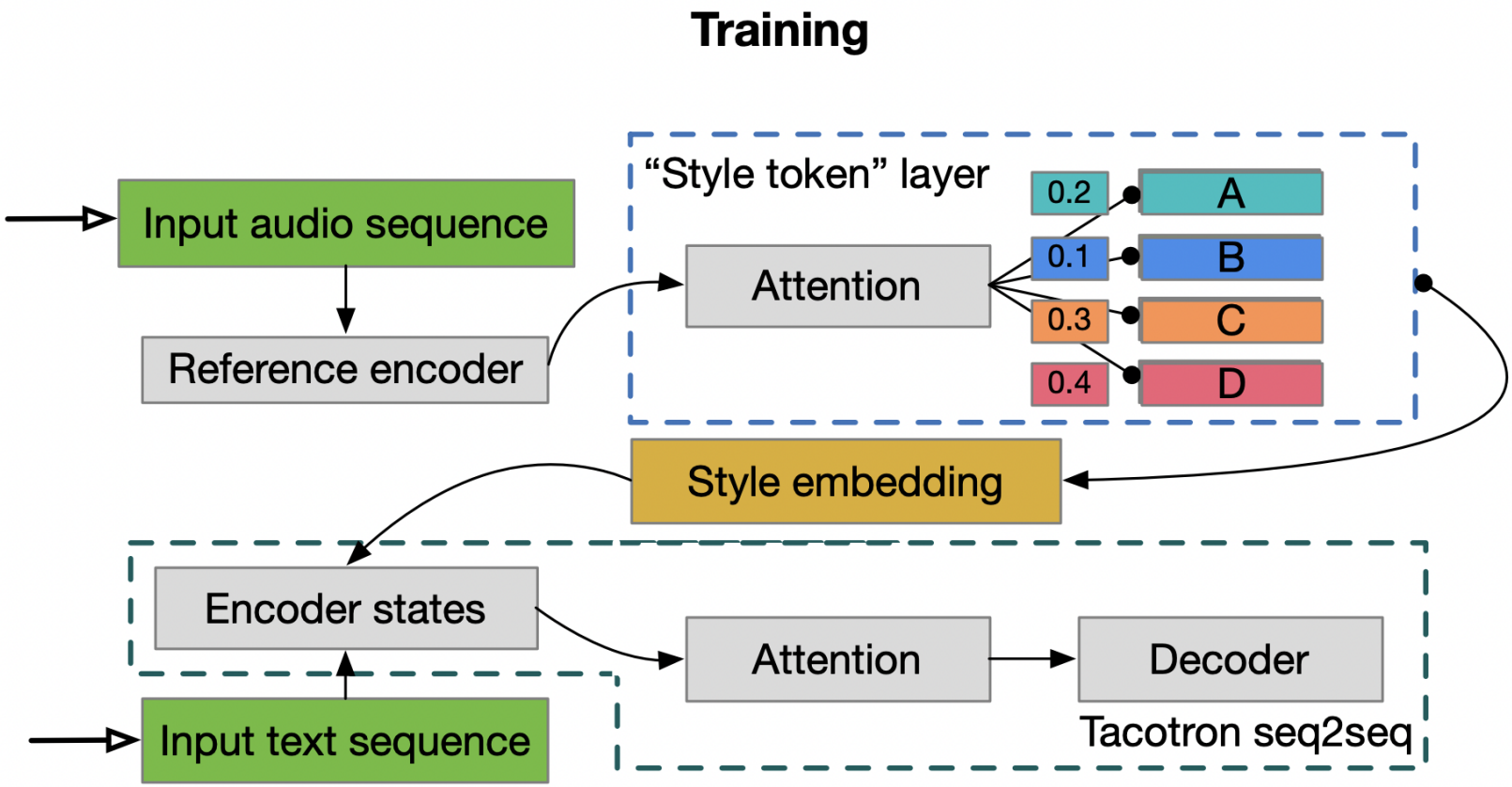

Figure: Log-mel spectrogram of the training target is fed to the reference encoder followed by a style token layer. The resulting style embedding is used to condition the Tacotron text encoder states

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Wang et al., Style Tokens: Unsupervised Style Modeling, Control and Transfer in End-to-End Speech Synthesis, International Conference on Machine Learning, 2018

Global Style Token (GST)

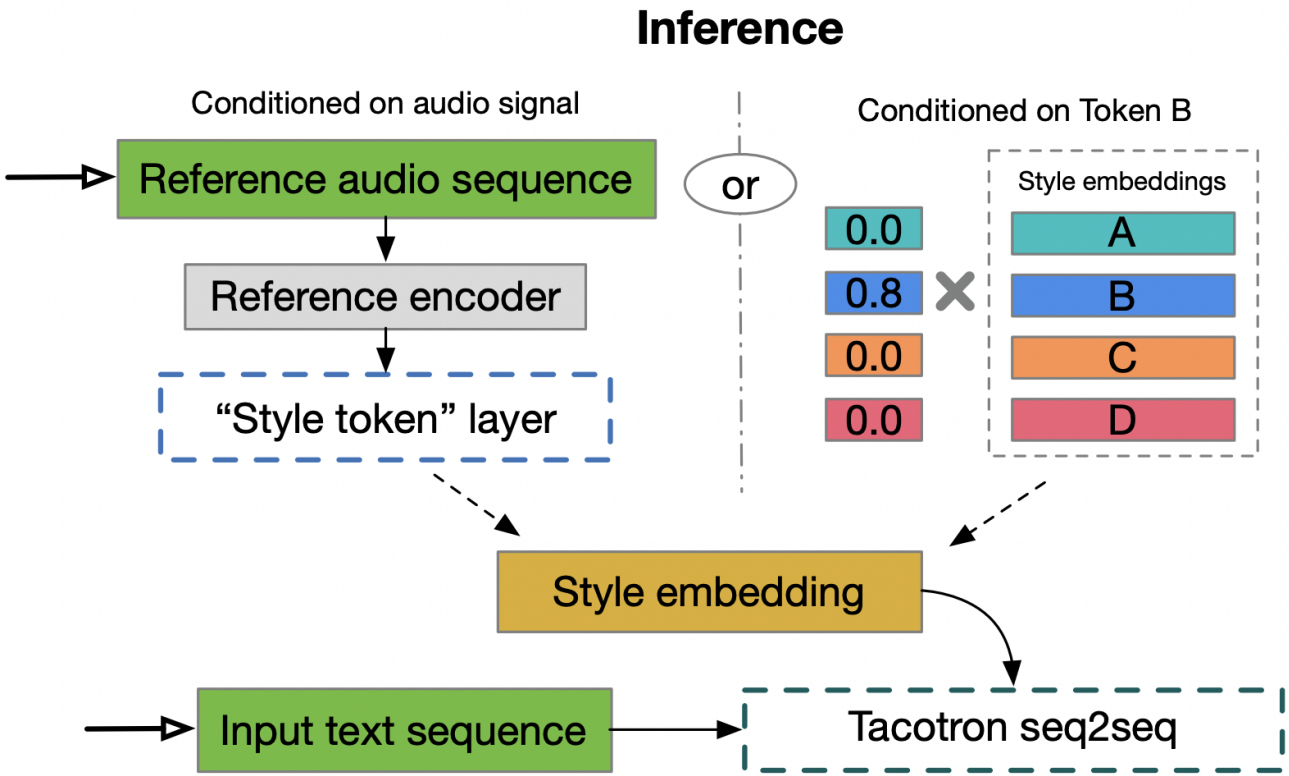

Figure: Inference: can feed an arbitrary reference signal to synthesize text with its speaking style. Alternatively, can remove the reference encoder and directly control synthesis using the learned interpretable tokens.

Wang et al., Style Tokens: Unsupervised Style Modeling, Control and Transfer in End-to-End Speech Synthesis, International Conference on Machine Learning, 2018

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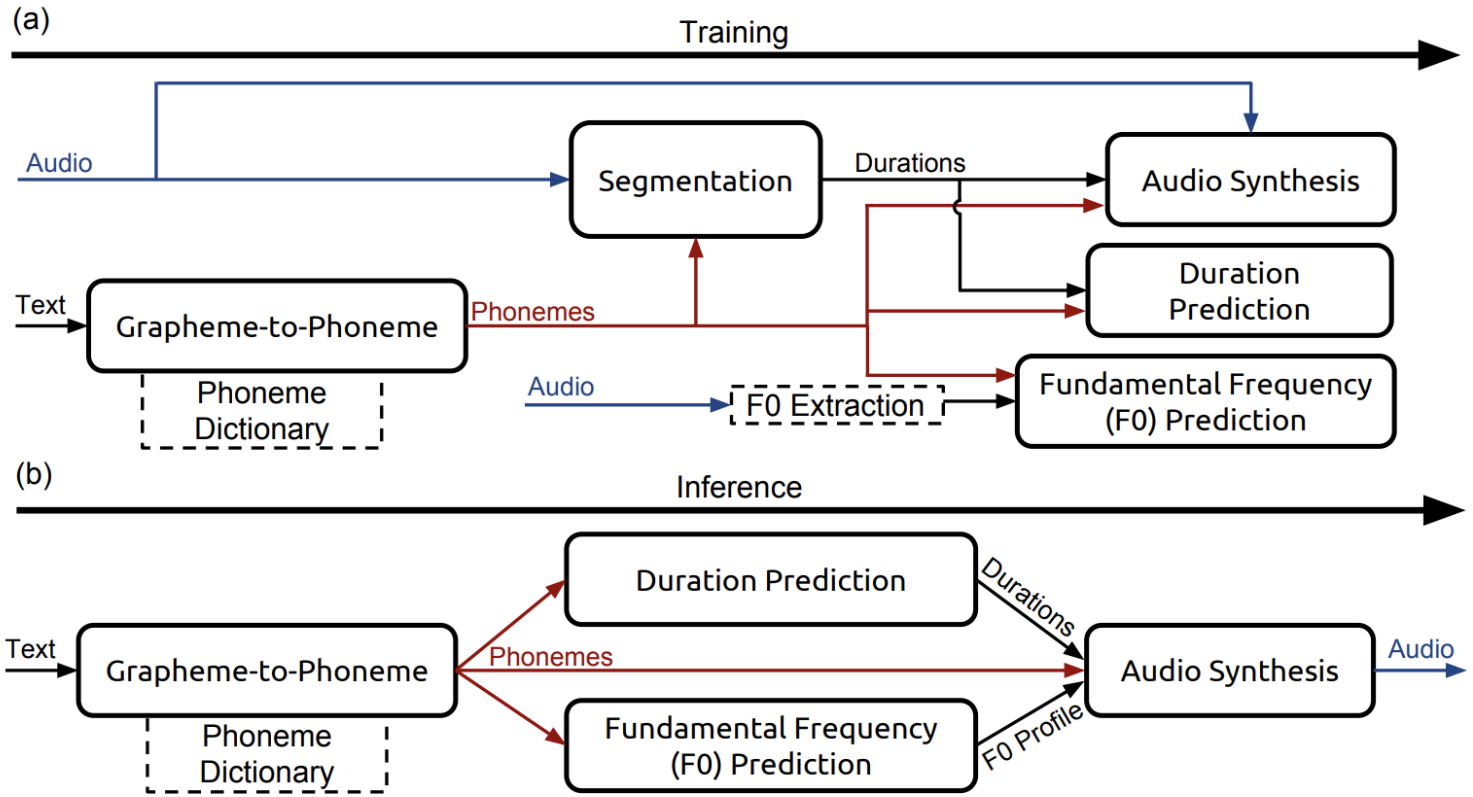
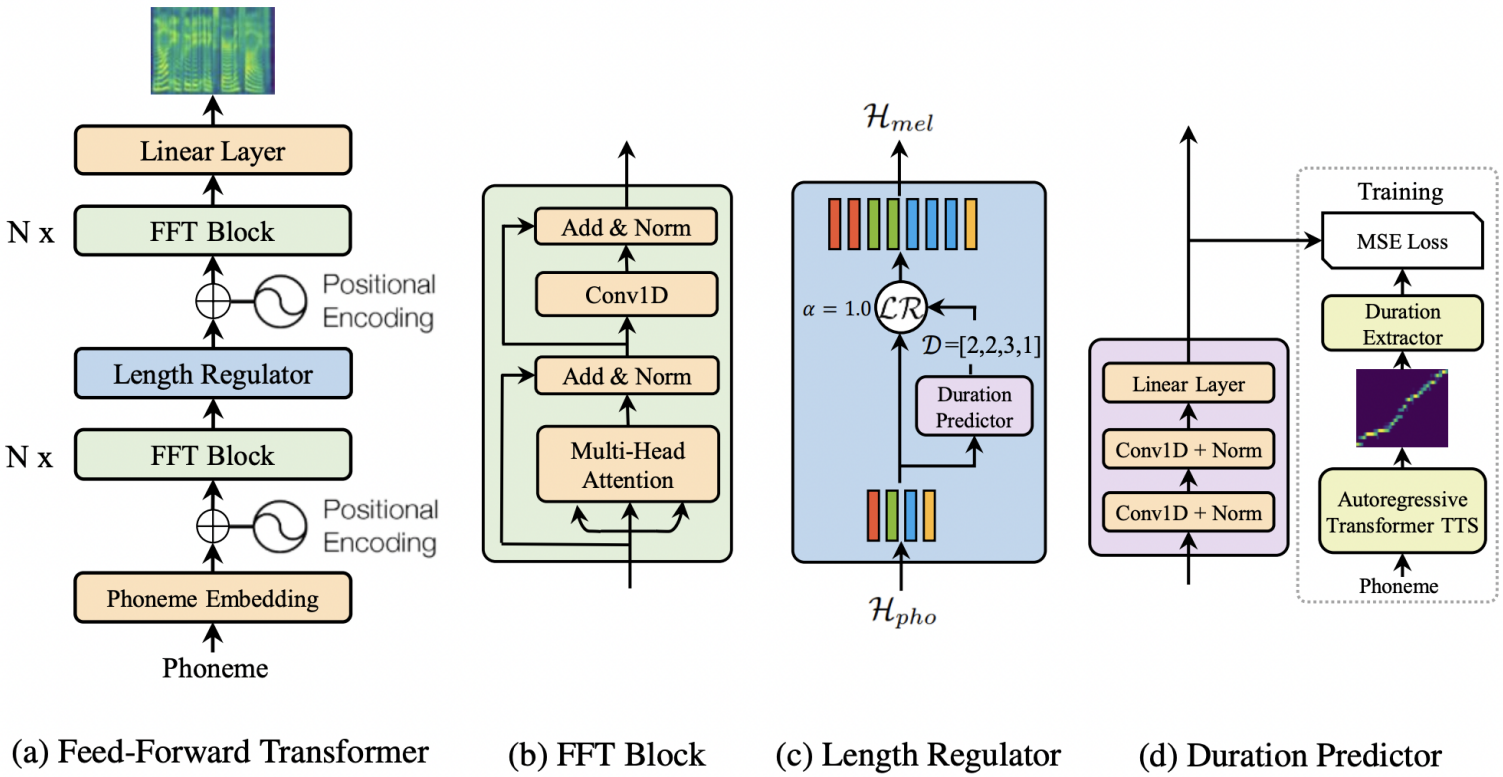
DeepVoice



- Grapheme-to-phoneme model – for words not present in a phoneme dictionary
- Segmentation model identifies where in the audio each phoneme begins and ends

Arik et al., Deep Voice: Real-time Neural Text-to-Speech, ArXiv preprint, 2017

FastSpeech



(a) Feed-Forward Transformer (b) FFT Block (c) Length Regulator (d) Duration Predictor

- Use of feed-forward Transformer (FFT) blocks
- Extract attention alignments from an encoder-decoder based teacher model for phoneme duration prediction

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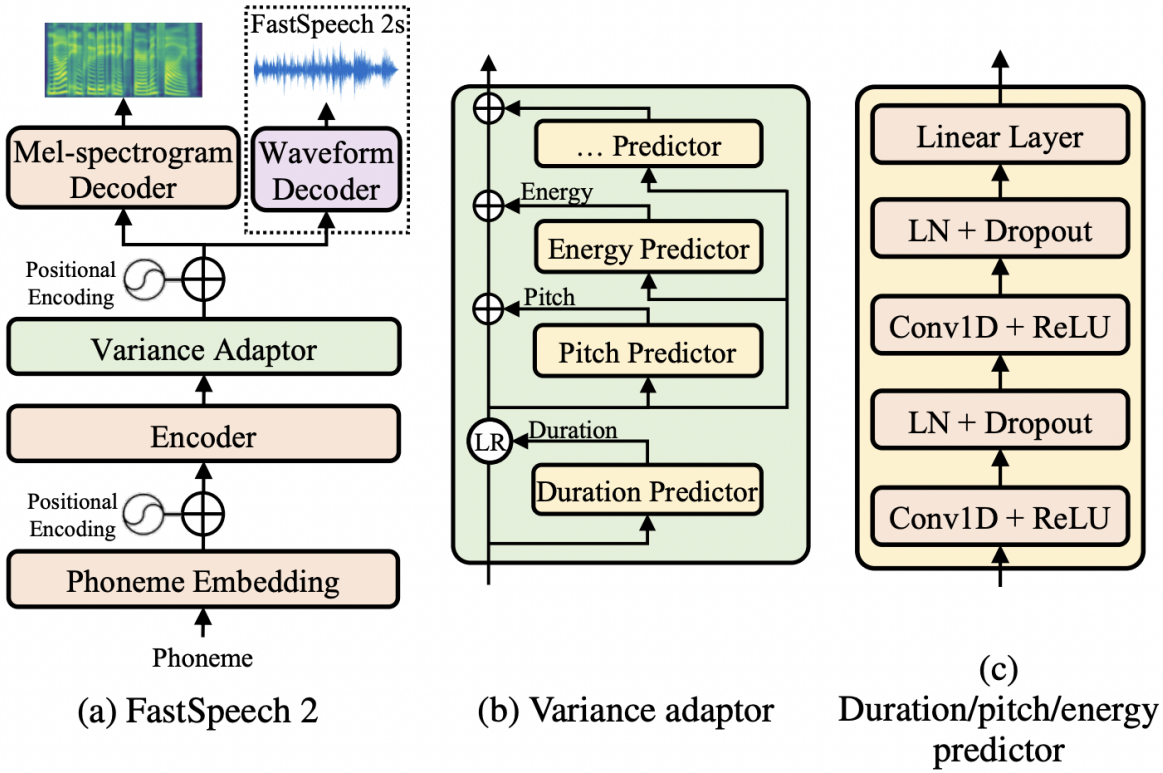
Yi et al., FastSpeech: fast, robust and controllable text to speech, Proceedings of the 33rd International Conference on NIPS, 2019

FastSpeech vs Tacotron

	Tacotron	**Fastspeech**
Inference speed	Slow	Fast
Synthesized speech is robust?	No, some words are skipped or repeated	Yes
Controllability (voice speed or prosody control)	Lack	Adjust voice speed smoothly

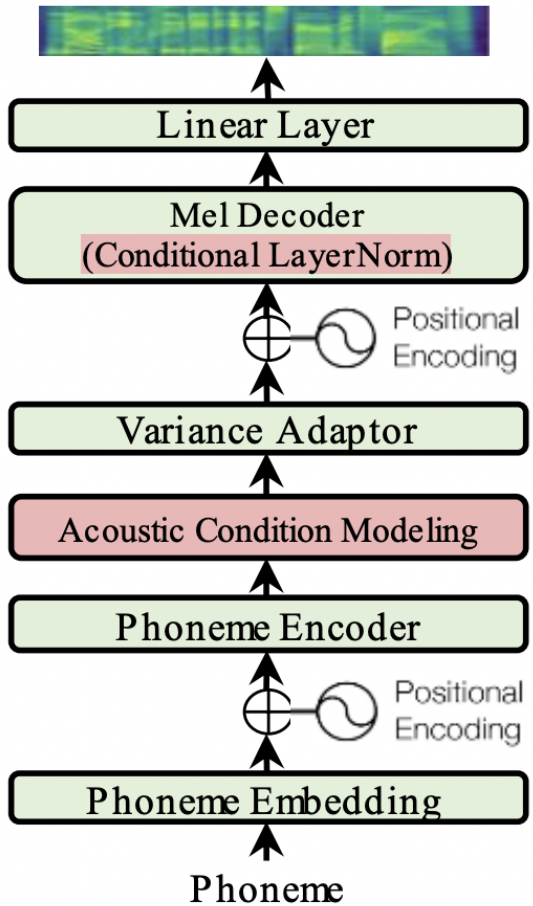
FastSpeech 2



- Directly training the model with ground-truth target instead of the simplified output from teacher
- more information of speech used as conditional inputs: duration, pitch (emotions), energy (volume and prosody)

Ren, Yi et al. FastSpeech 2: Fast and High-Quality End-to-End Text to Speech, Arxiv preprint, 2021

AdaSpeech



- Adopted FastSpeech 2
- Add acoustic condition modeling

Chen et al., AdaSpeech: Adaptive Text to Speech for Custom Voice, Arxiv preprint, 2021

AdaSpeech: acoustic condition modeling

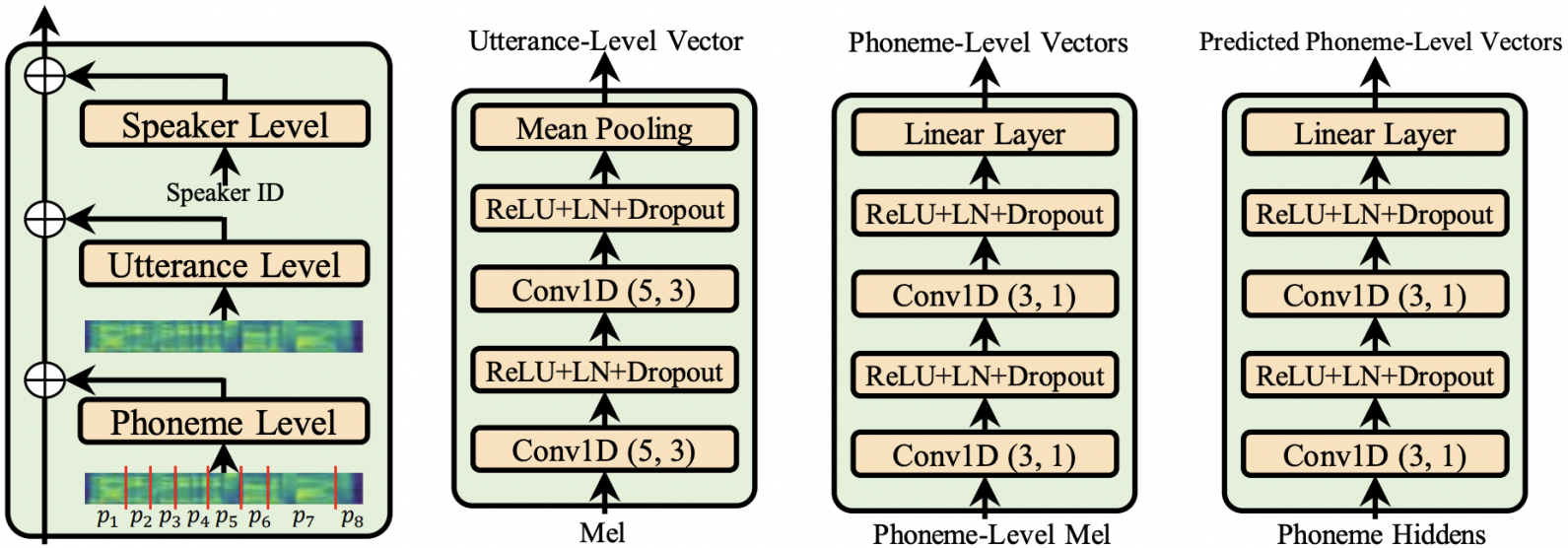


Figure: Adding acoustic conditions such as speaker timbre, prosody and recording environments into model

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Chen et al., AdaSpeech: Adaptive Text to Speech for Custom Voice, Arxiv preprint, 2021