Topics on Neural Speech Synthesis

Vassilis Tsiaras
University of Crete

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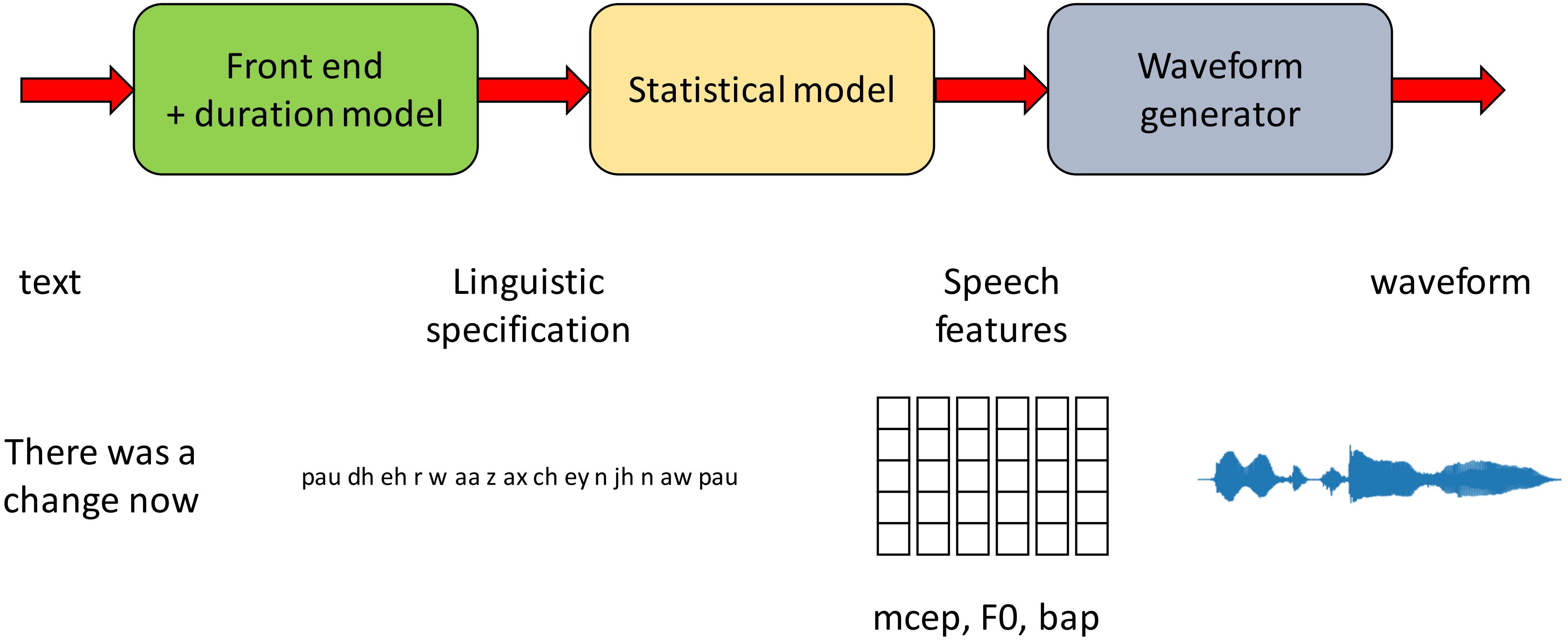
Outline

- Introduction
- Two stage pipeline systems
  - Acoustic models
    - Tacotron 2
    - Transformer TTS
    - FastSpeech 1 and 2
  - Neural vocoders
    - Sequential generation
      - WaveNet
      - WaveRNN
    - Parallel generation
      - Artifacts
- Do end-to-end systems reduce the artifacts in parallel generation?
- Neural audio codec
- Speech synthesis with language models

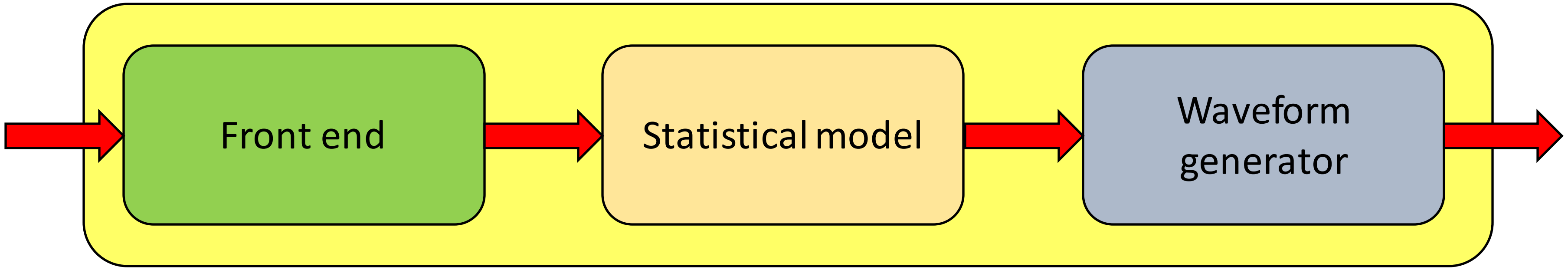
Introduction

- Traditional Text-To-Speech (TTS) systems are based on multi-stage, hand-engineered pipelines
- Neural network-based TTS models outperform conventional concatenative and statistical parametric approaches in terms of speech quality.
- Most popular neural network-based TTS systems have two-stage pipelines.
    1. Generate mel-scale spectrograms from text input.
    2. Synthesize speech from the generated mel-spectrograms using a separately trained neural vocoder.
- Also, there are End-to-end neural network-based TTS system.
    - Trained on <text, audio> pairs with minimal human annotation and effort.
- However, end-to-end models are harder to train and require a large number of high-quality recordings with transcriptions.

The classic three-stage pipeline of statistical parametric speech synthesis



The end-to-end problem

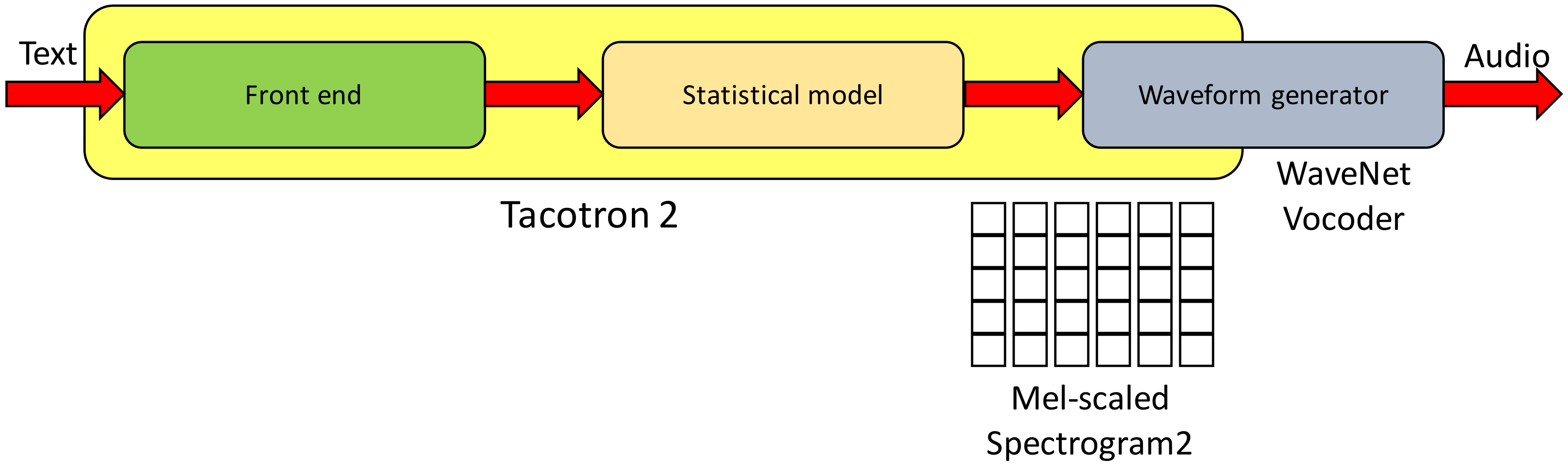


text

waveform

There was a
change now

Tacotron 2: A two stage pipeline



- **Tacotron 2** produces mel-scaled spectrograms, which are used as local conditioning to a WaveNet vocoder.

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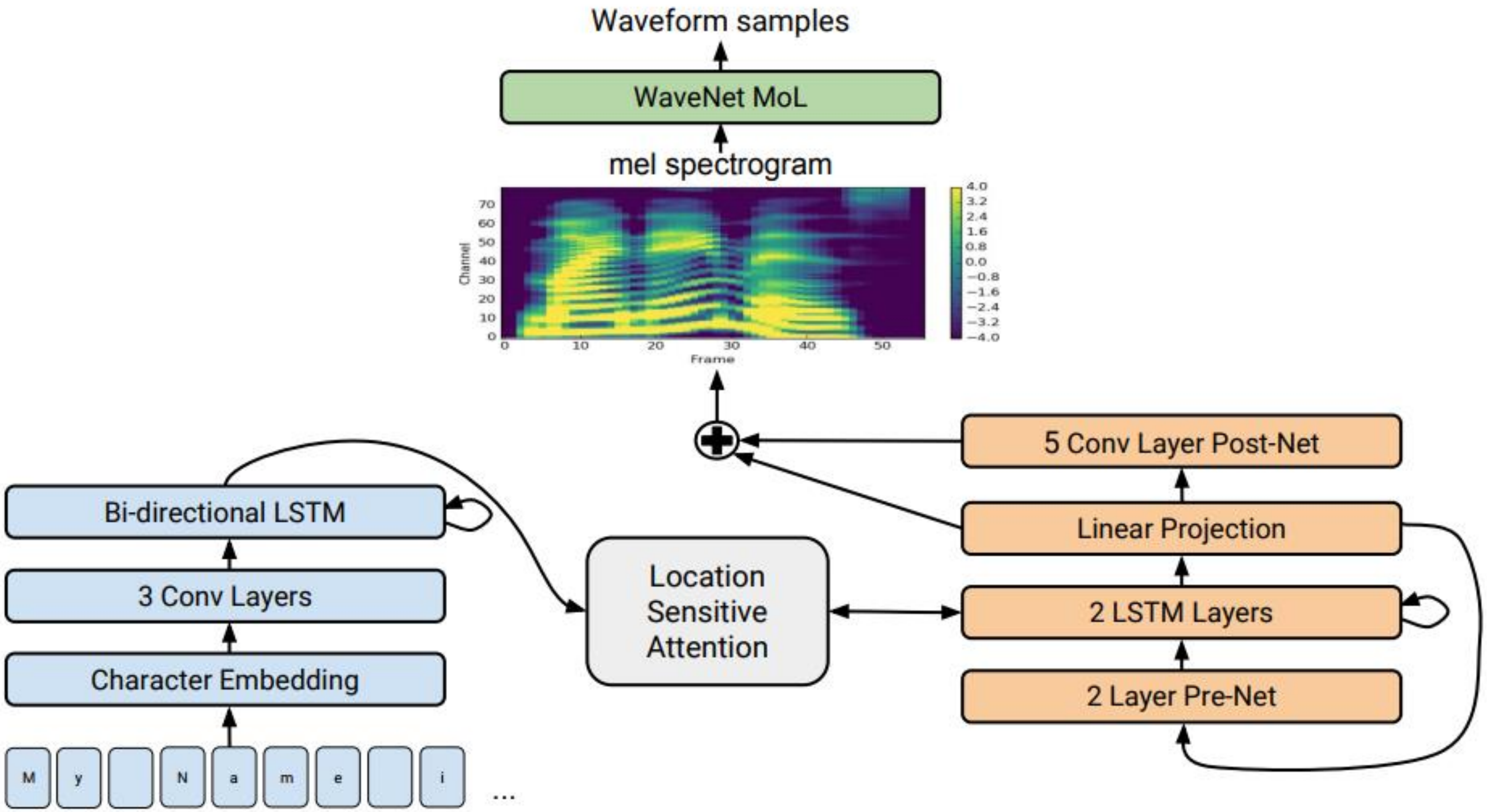
      - WaveNet
      - WaveRNN
    - Parallel generation
      - Artifacts

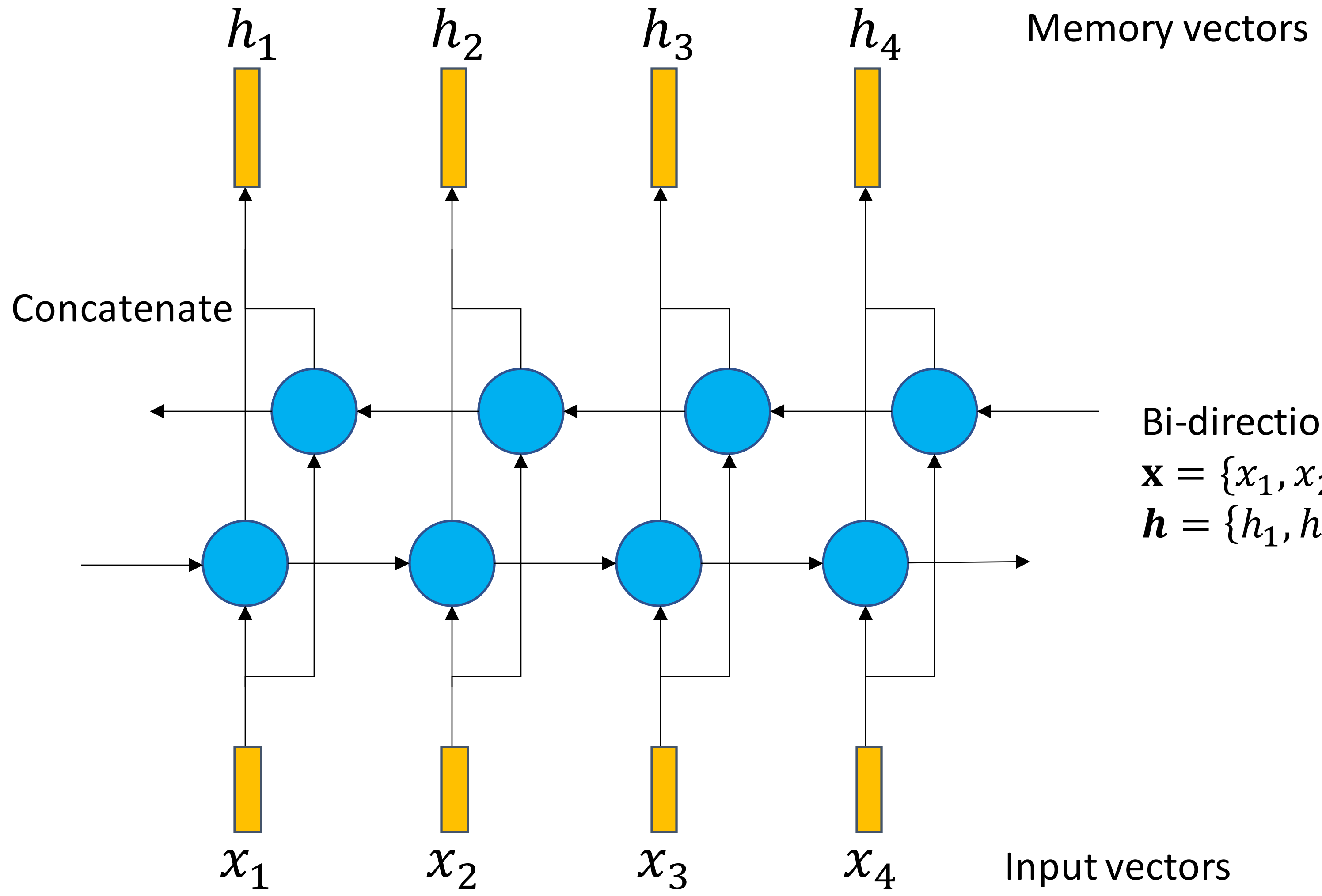
- Do end-to-end systems reduce the artifacts in parallel generation?

Tacotron 2 – A Sequence-to-Sequence model

- Tacotron 2 maps a sequence of letters to a sequence of 80-dimensional Mel-scaled spectrograms.
- Finally these spectrograms are converted to waveform using a WaveNet-like architecture.



Encoder

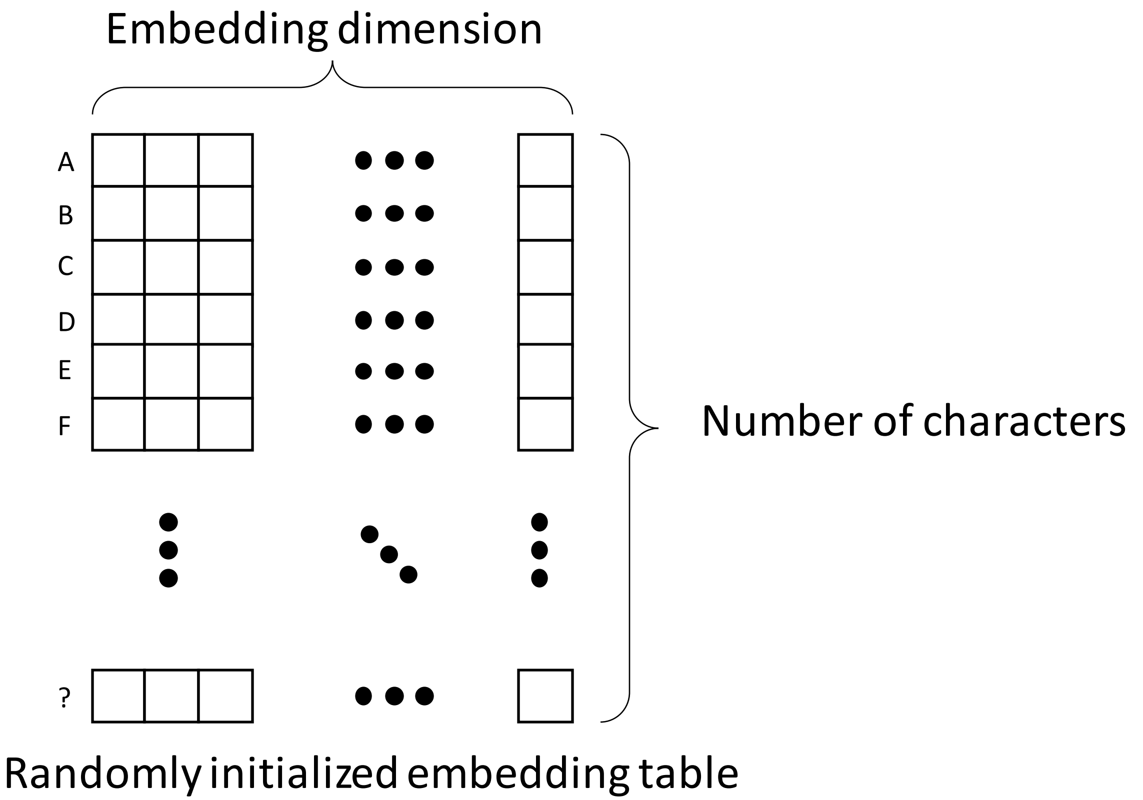


Bi-directional RNN based encoder takes the input sequence $\mathbf{x} = \{x_1, x_2, \dots, x_T\}$ and outputs the hidden states $\boldsymbol{h} = \{h_1, h_2, \dots, h_T\}$ (memory vectors).

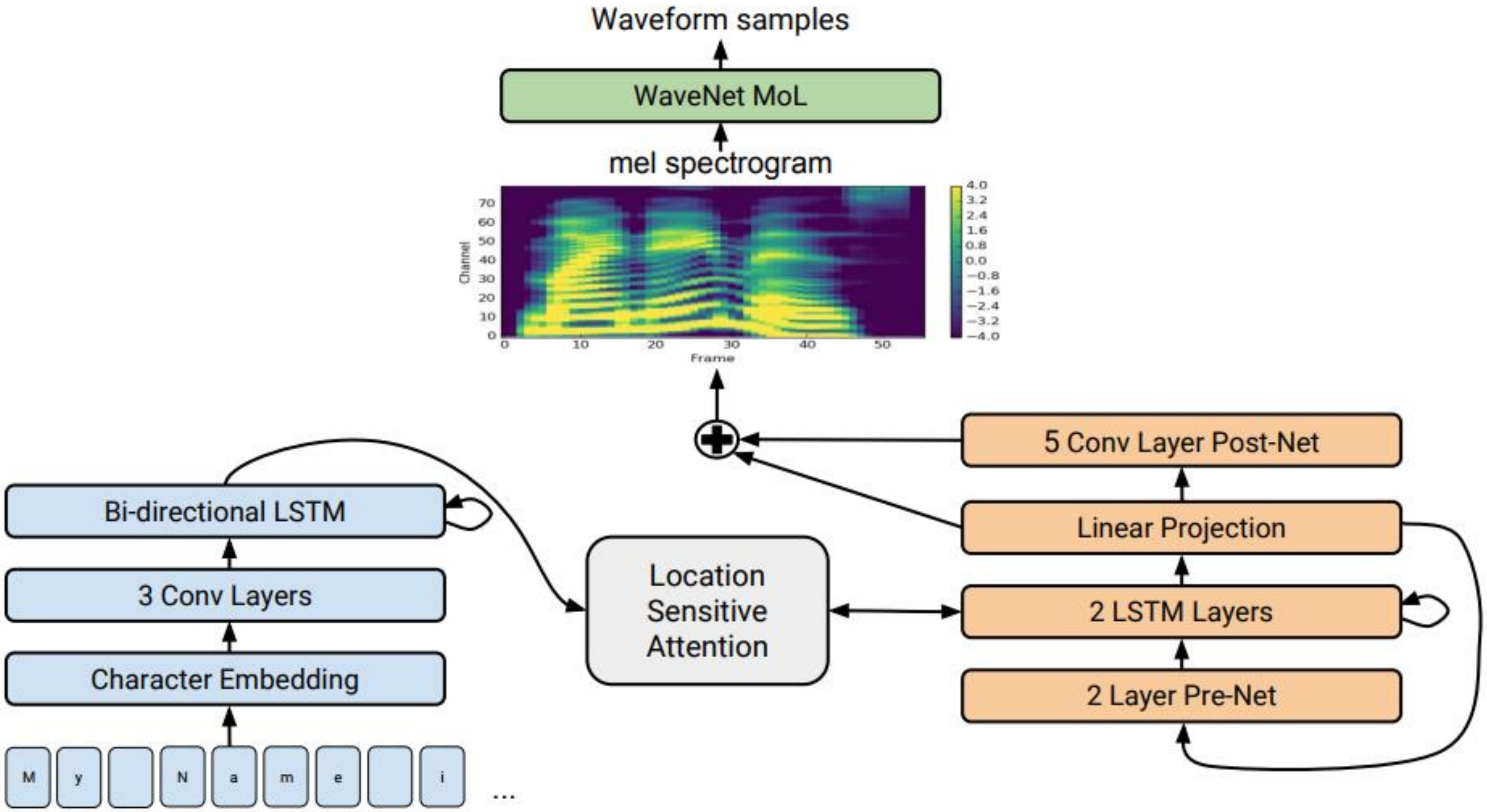
Note that a memory vector does not directly depend on the other memory vectors.
The RNNs in the implementation of the encoder extend the receptive field of a memory vector to the whole input sequence.
However, the use of RNNs prevent the parallel generation of the memory vectors.

Encoder: Character embedding

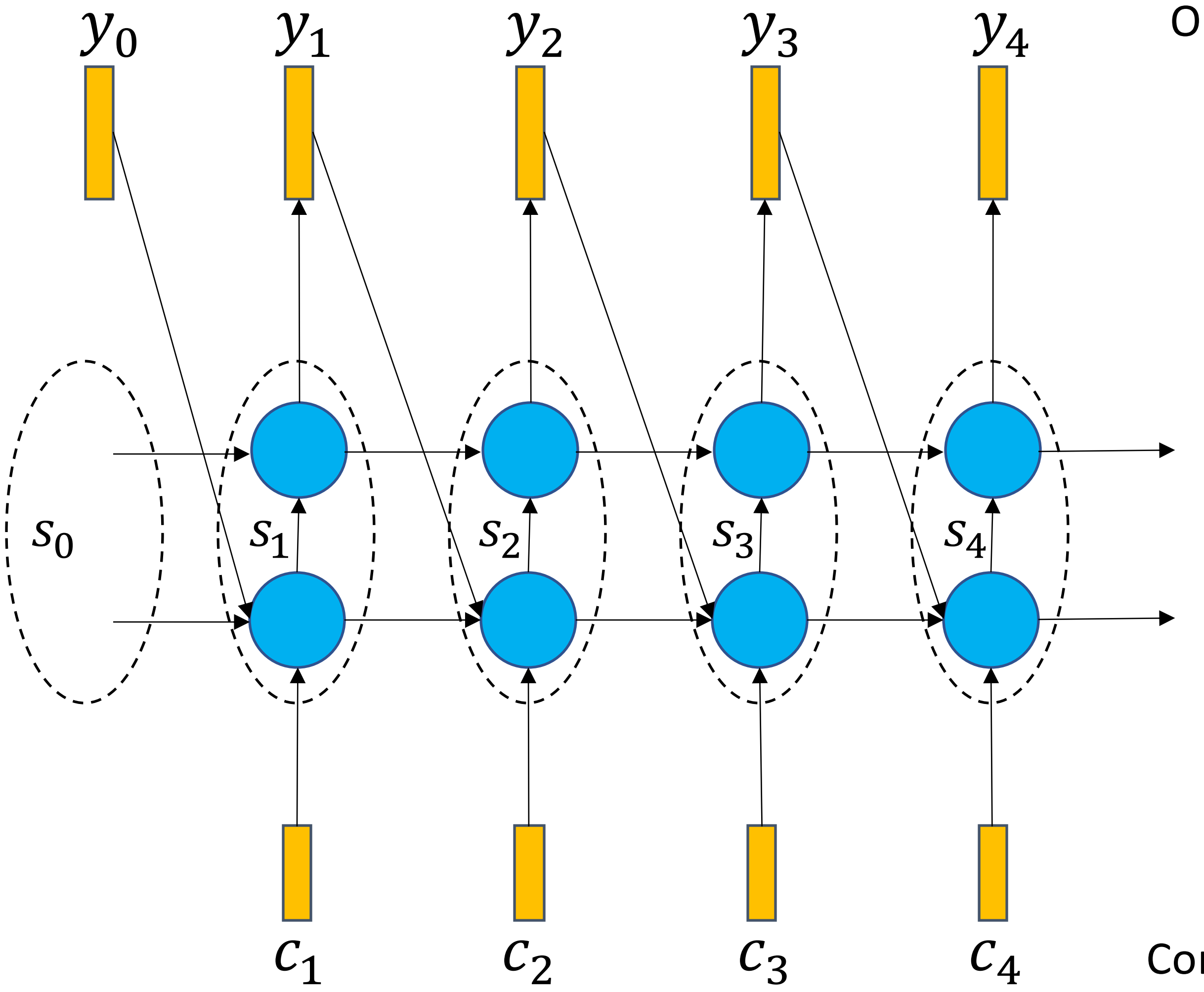
- Input characters are represented using a learned 512-dimensional character embedding.



Decoder: An autoregressive module



Decoder: Unrolling in time



Output vectors

$$s_i = Decoder(s_{i-1}, y_{i-1}, c_i)$$

$$y_i = OutputFunction(s_i)$$

Usually, a stack of two unidirectional RNNs

Context vectors which depend on the memory vectors of encoder

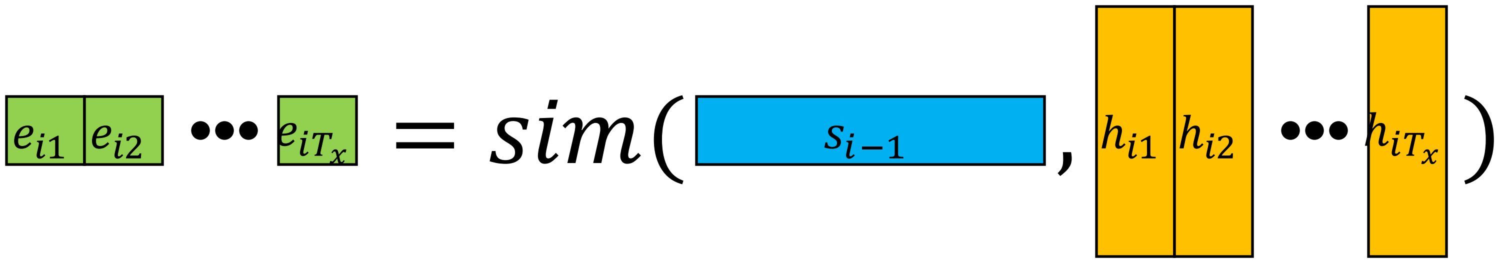
At each decoder output step i, inputs to the RNN cell are s_{i-1}, y_{i-1} and the context c_i and outputs the vectors s_i and y_i.

The attention mechanism

1. Alignment scores:

- The alignment model takes the encoded hidden states, h_j, and the previous decoder output, s_{i-1}, to compute a score, e_{ij}
- The score indicate how well the elements of the input sequence align with the current output at position, i

$$e_{ij} = sim(s_{i-1}, h_j), \qquad j = 1, \dots, T_x$$



2. Alignment weights or probabilities:

- The weights, a_{ij}, are computed by applying a softmax operation to the previously computed alignment scores:

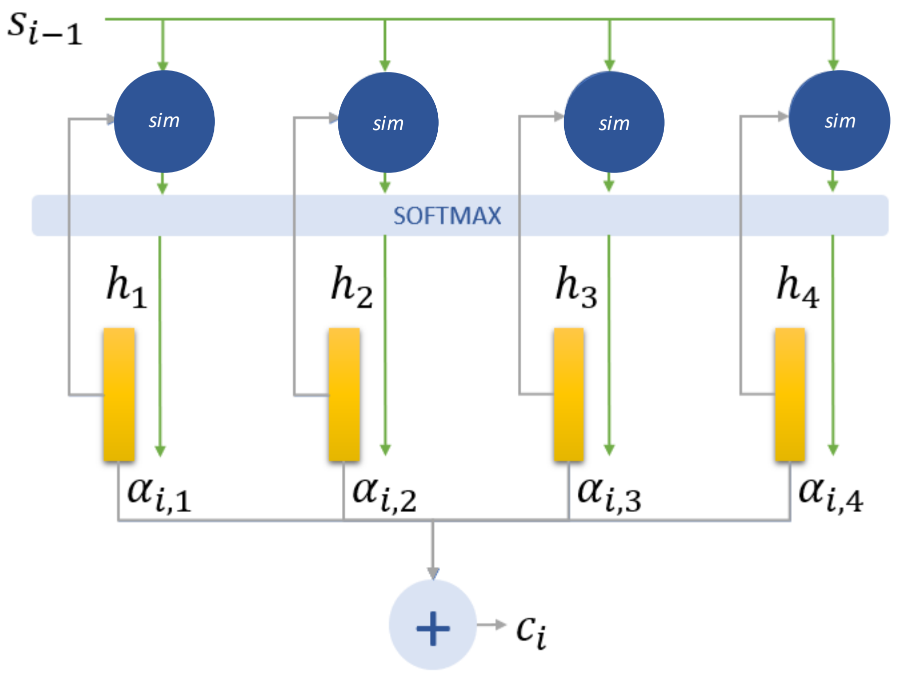
$$[a_{i1}, a_{i2}, \dots, a_{iT_x}] = softmax([e_{i1}, e_{i2}, \dots, e_{iT_x}]) = \frac{1}{Z}[\exp(e_{i1}), \exp(e_{i2}), \dots, \exp(e_{iT_x})], \qquad Z = \sum_{k=1}^{T_x} \exp(e_{ik})$$

The attention mechanism

3. Context vector

- A unique context vector, c_i, is fed into the decoder at each time step. It is computed by a weighted sum of all, T_x, encoder hidden states:

$$c_i = \sum_{j=1}^{T_x} a_{ij} h_j$$



Attention mechanisms

- Dot product attention (Luong)

  $$sim(s_{i-1}, h_j) = s_{i-1}^T h_j$$

- Multiplicative attention

  $$sim(s_{i-1}, h_j) = s_{i-1}^T W h_j$$

- Additive attention (Bahdanau)

  $$sim(s_{i-1}, h_j) = w^T \tanh(W_s s_{i-1} + W_h h_j + b)$$

- Location sensitive additive attention

  $$sim(s_{i-1}, h_j) = w^T \tanh(W_s s_{i-1} + W_h h_j + W_f f_{ij} + b)$$

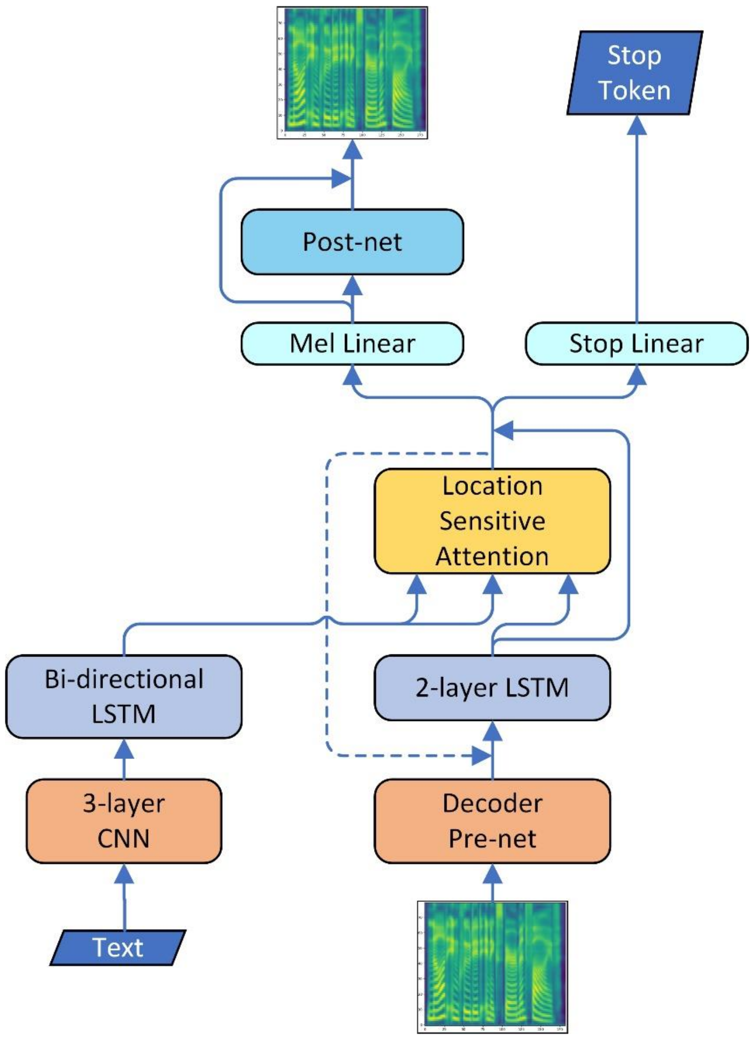
  $$\boldsymbol{f}_i = F * \boldsymbol{a}_{i-1}, \quad \text{where } \boldsymbol{a}_{i-1} = \left[a_{i-1,1}, \ldots, a_{i-1,T_x}\right]$$

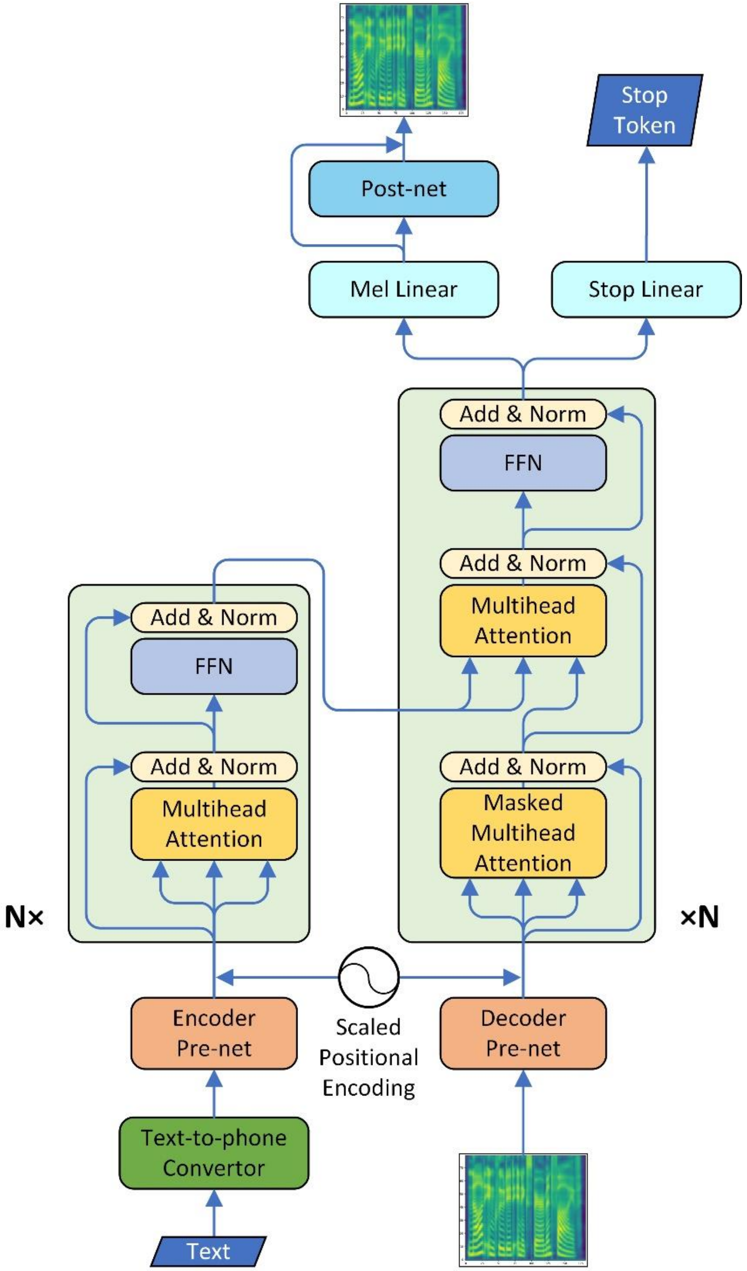
- Cumulative attention

  $$\boldsymbol{ca}_1 = \boldsymbol{a}_1, \qquad \boldsymbol{ca}_i = \boldsymbol{ca}_{i-1} + \boldsymbol{a}_i$$

- Monotonic attention

Tacotron 2 vs Transformer TTS

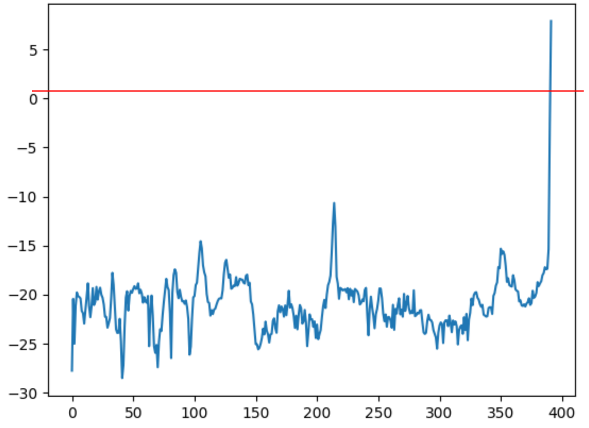




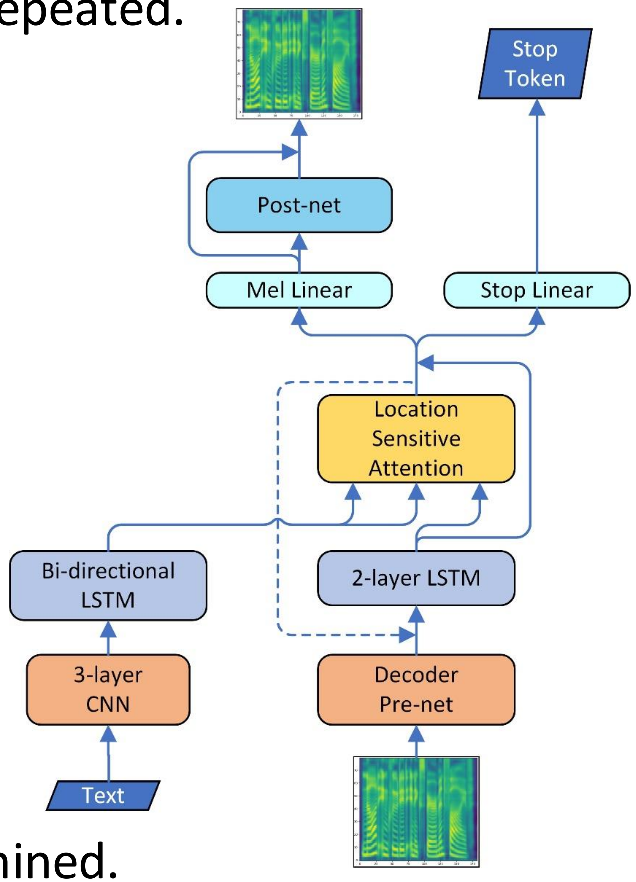
Issues with autoregressive acoustic models

- Tacotron and Transformer TTS face several challenges:
  - Slow inference speed for autoregressive generation.
  - Synthesized speech is usually not robust, with words being skipped and repeated.

Text: Bad speech synthesis



Stop token plot



- Lack of controllability since the generation length is automatically determined.
  - The voice speed and the prosody (such as word breaks) cannot be adjusted.

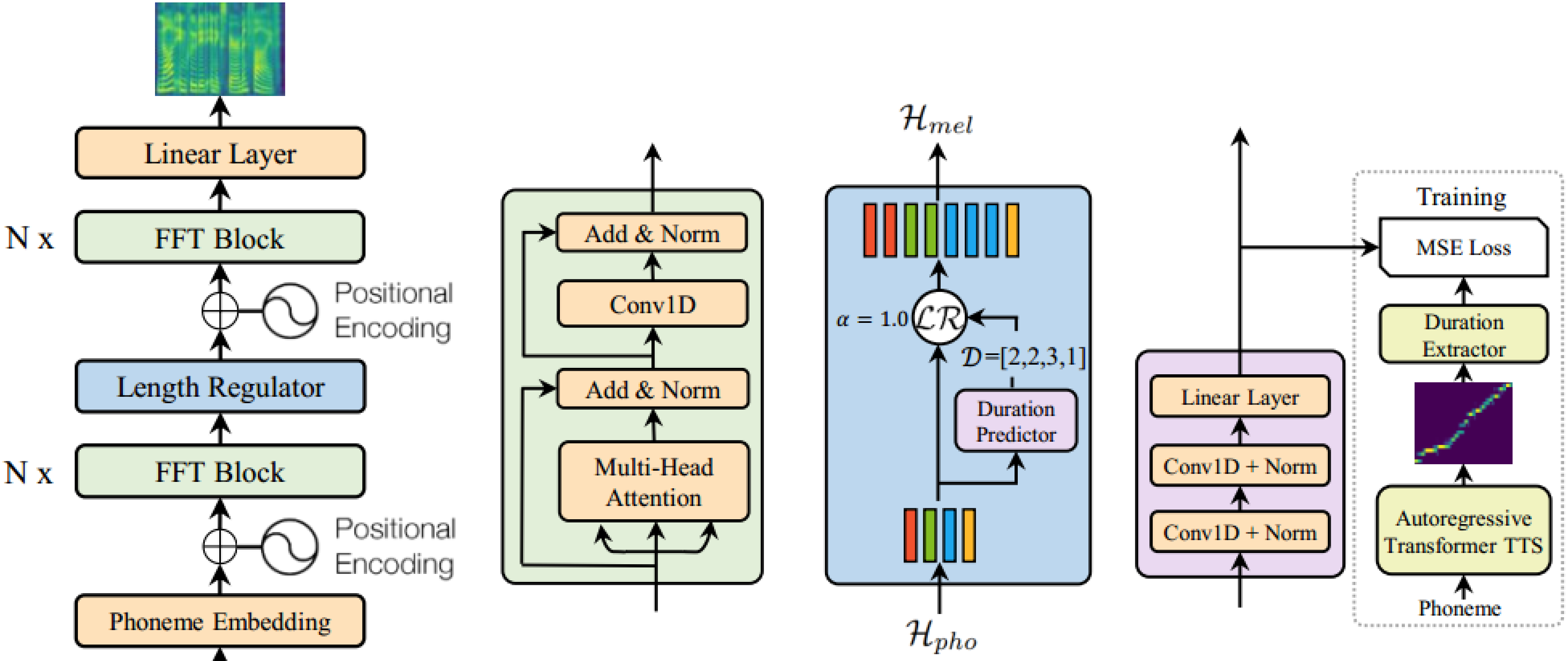
Non-autoregressive acoustic models

- Researchers from Microsoft and Zhejiang University propose FastSpeech.
  - Fast generation speed
  - Robustness
  - Controllability (?)
  - High quality (similar to autoregressive models, such as Tacotron 2 and Transformer TTS)

Text: Bad speech synthesis

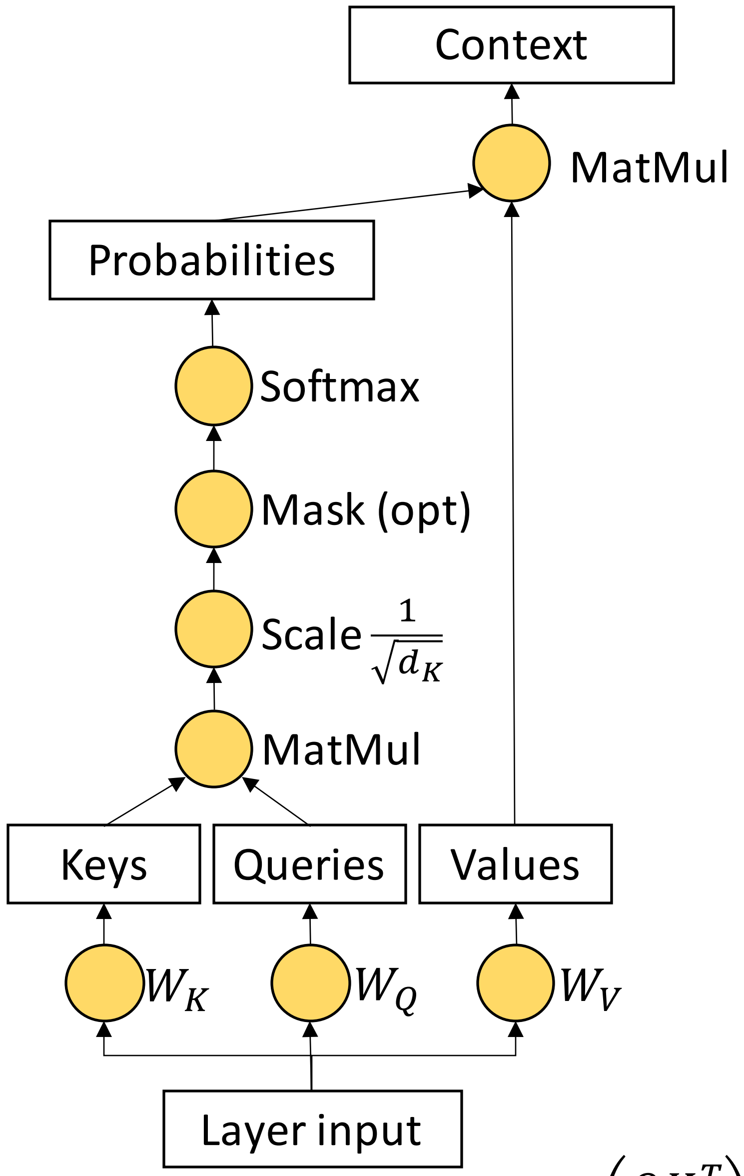
Created with TensorFlowTTS
with MelGAN vocoder

FastSpeech: Feed-Forward Transformer

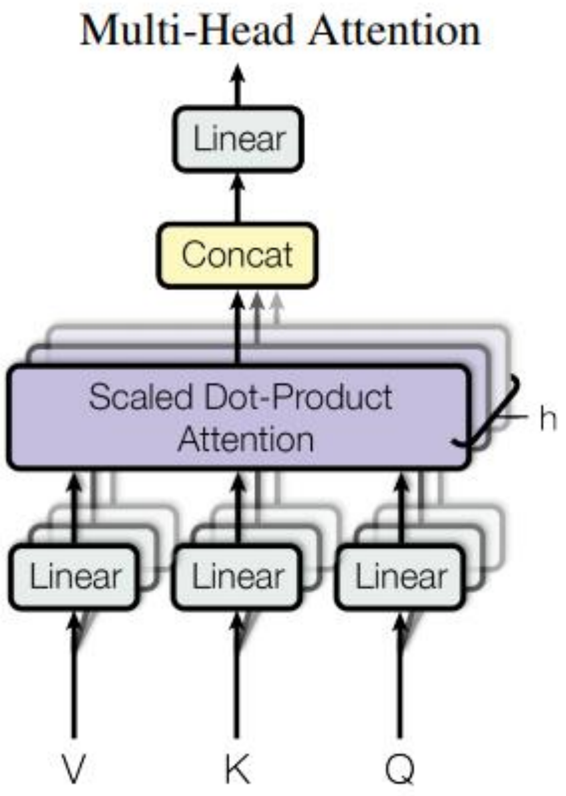


(a) Feed-Forward Transformer (b) FFT Block (c) Length Regulator (d) Duration Predictor

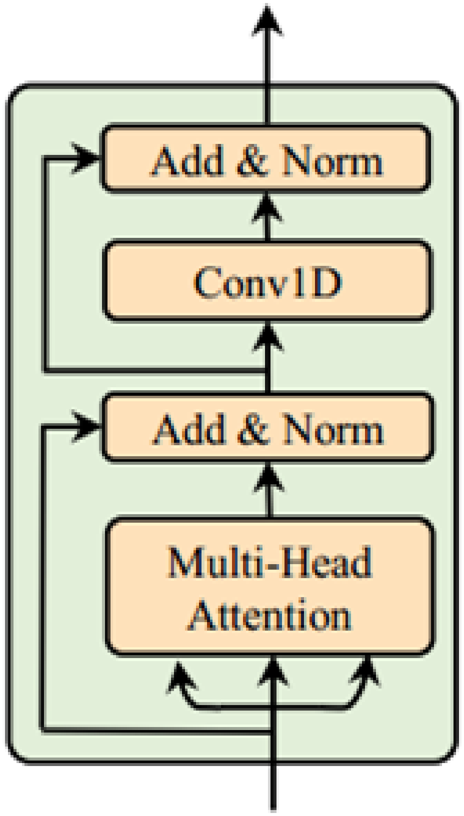
Scaled Dot-Product Multi-Head Attention



$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

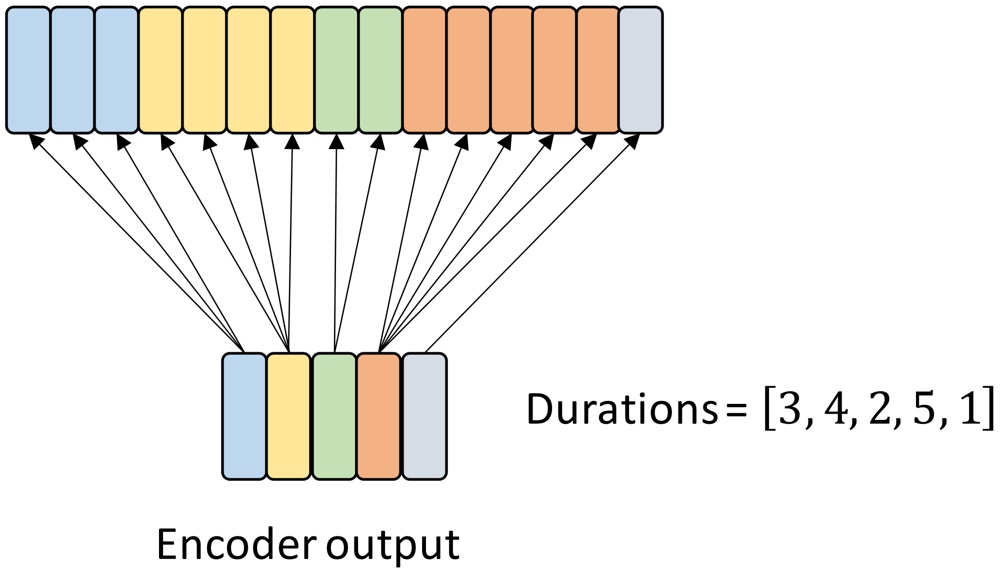


Attention heads=2

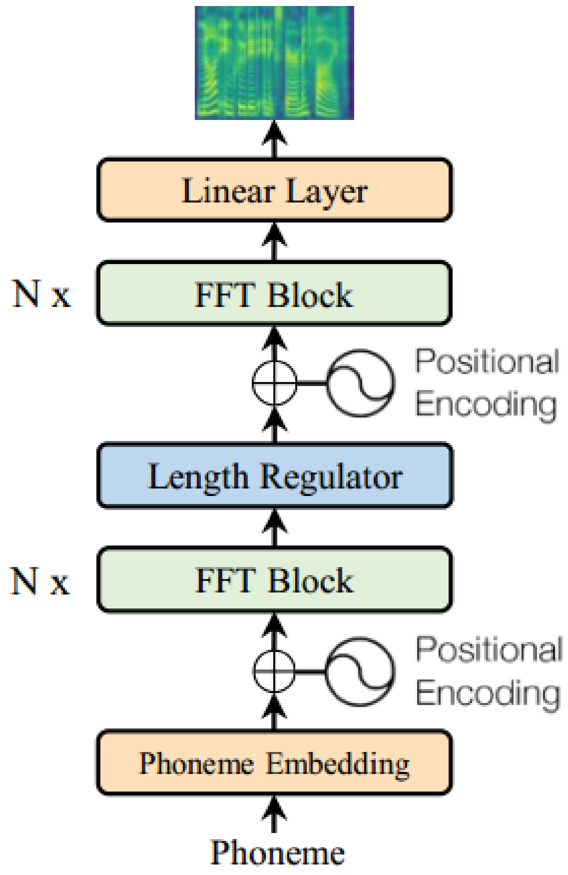


Length Regulator

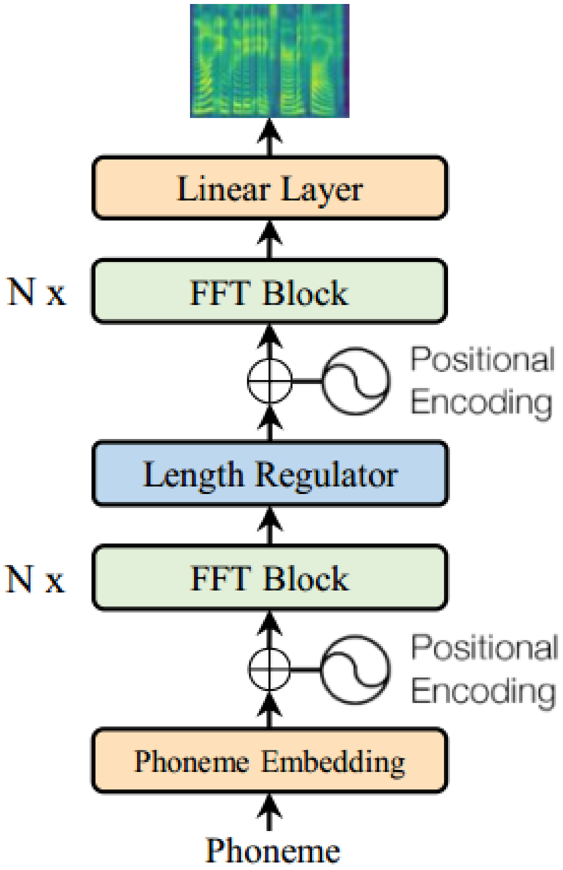
- Since the length of the phoneme sequence is smaller than that of the mel-spectrogram sequence, one phoneme corresponds to several mel-spectrograms.
- The number of mel-spectrograms that aligns to a phoneme is called phoneme duration.
- The length regulator expands the hidden sequence of phonemes according to the duration in order to match the length of a mel-spectrogram sequence.

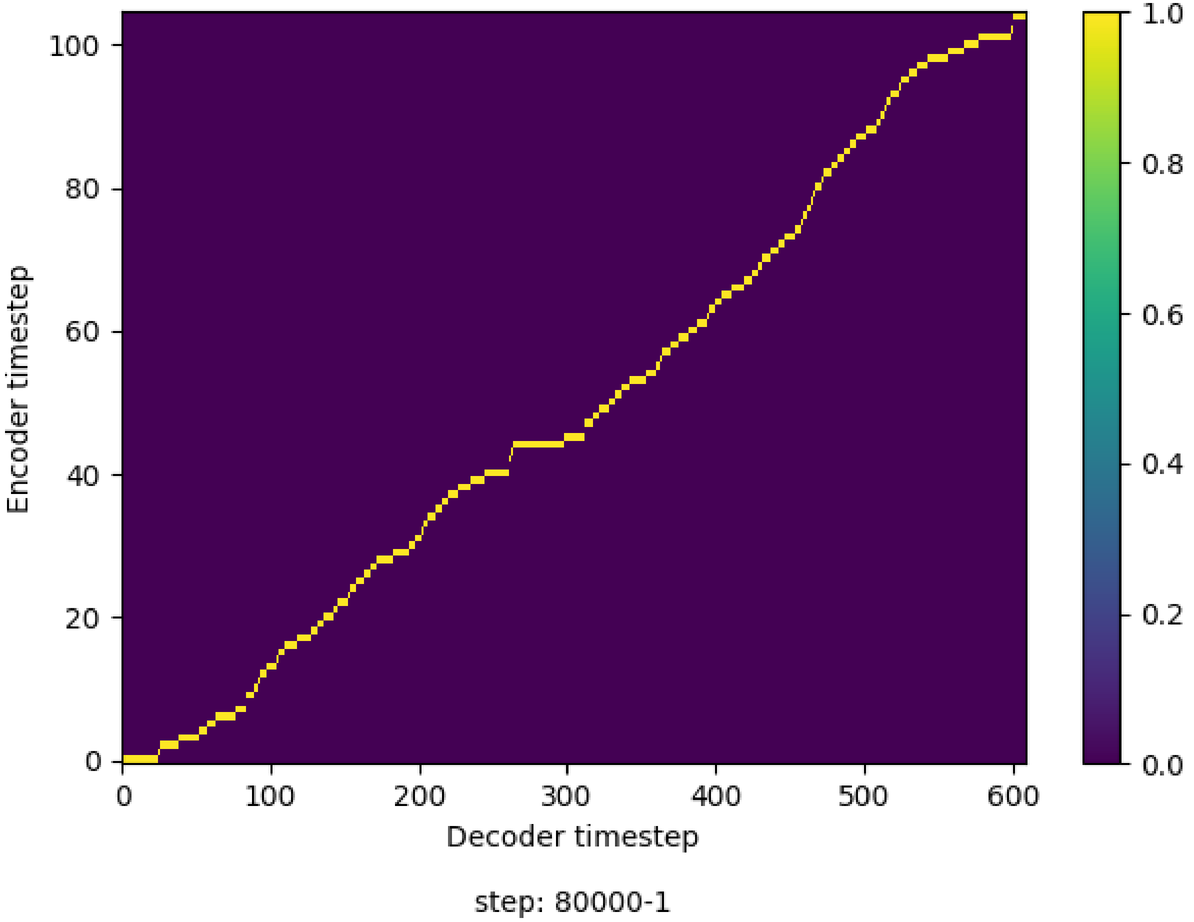


FastSpeech: Feed-Forward Transformer



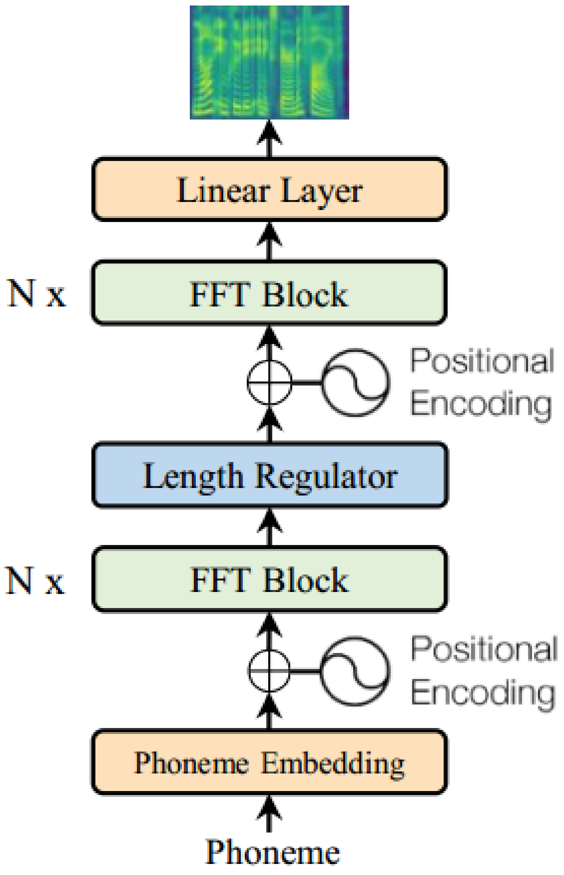
FastSpeech: Feed-Forward Transformer

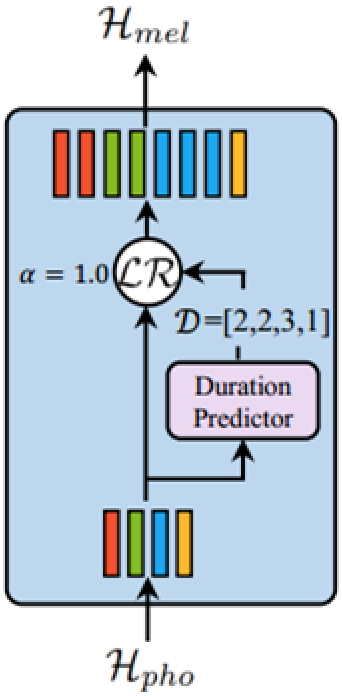




Loss functions

- Mel-loss: Usually the mean-absolute or the mean-square error between the ground-truth mels and the predicted-mels.
- Duration-loss: Mean square error between the ground-truth log-duration and the predicted log-duration.

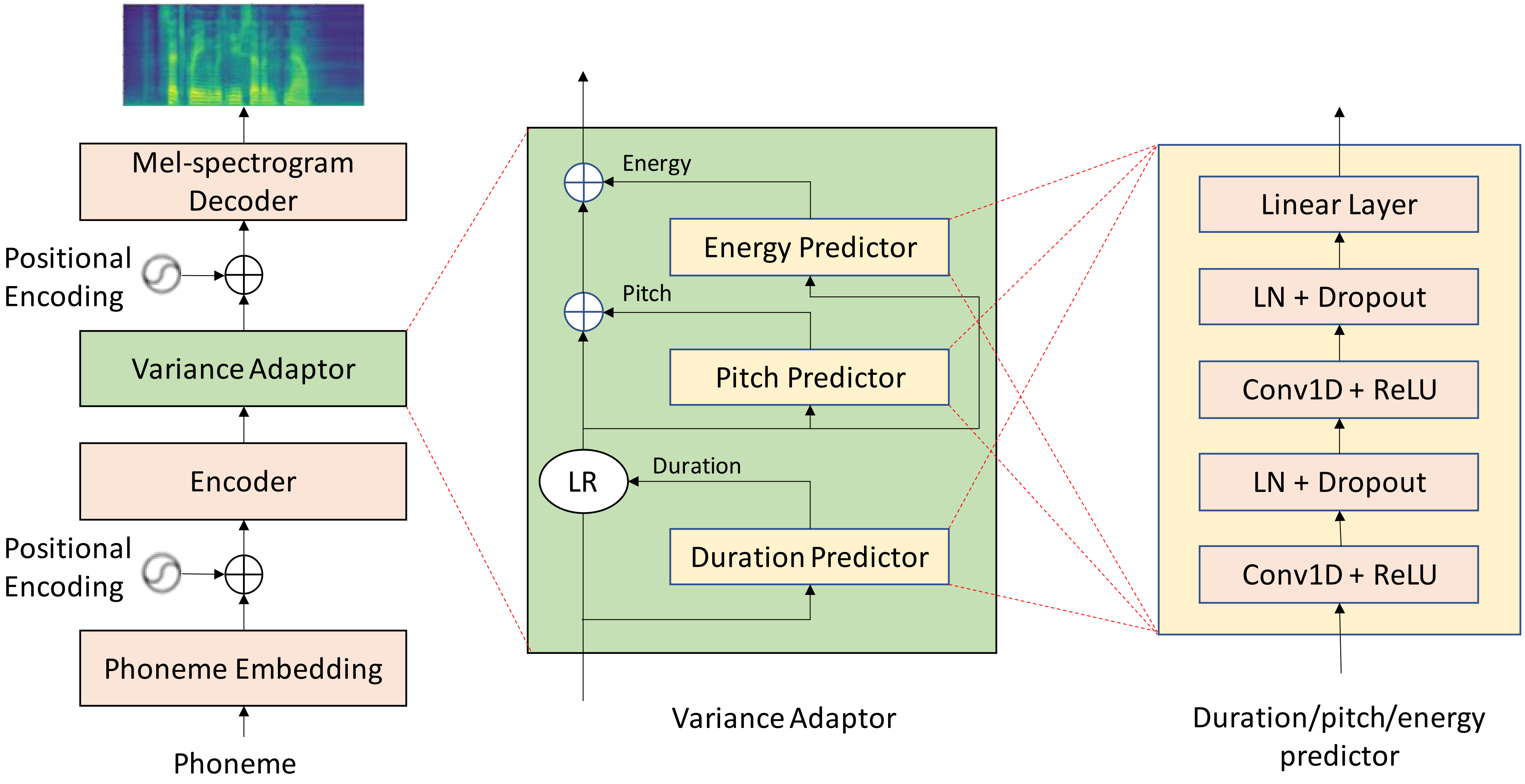




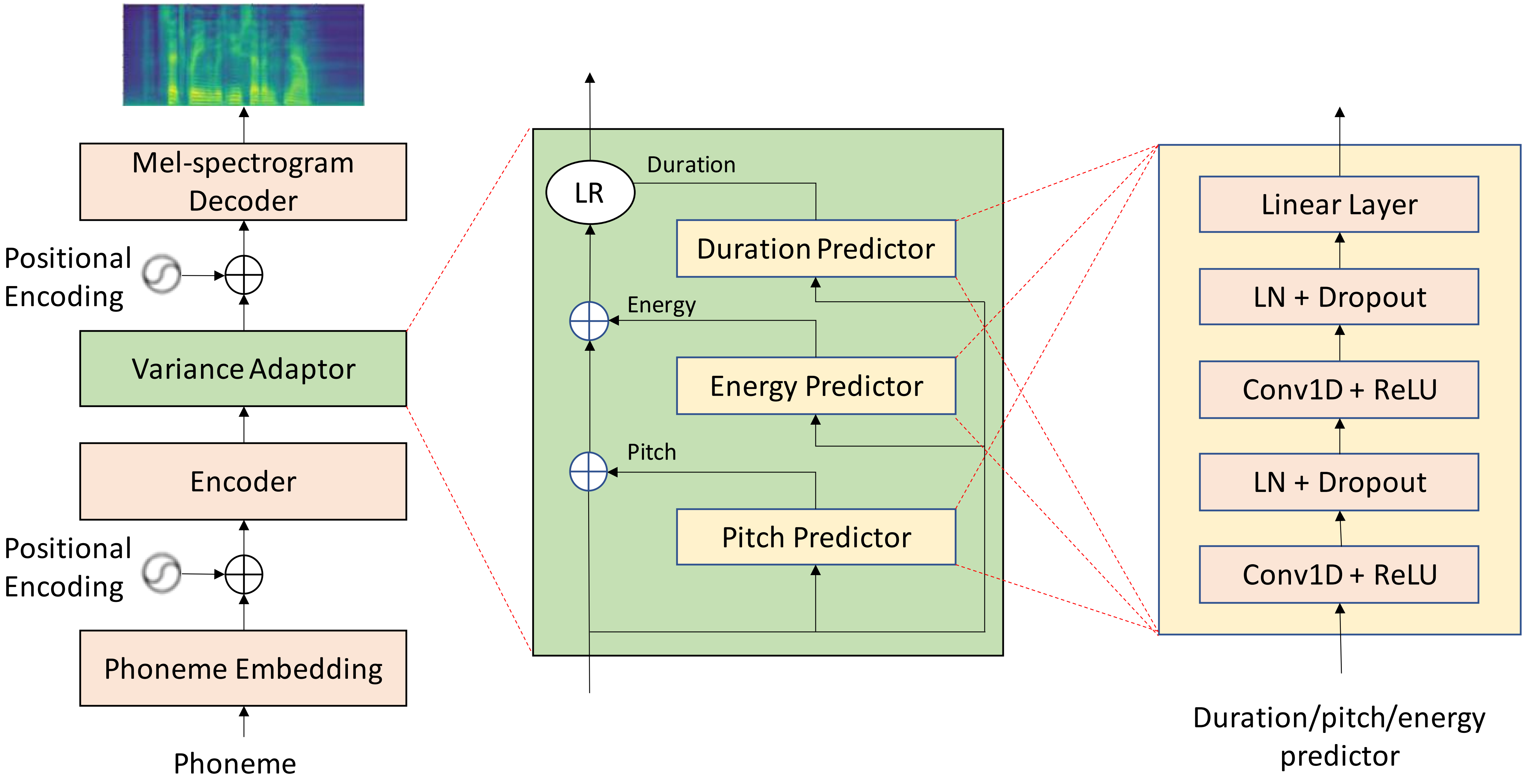
FastSpeech 2

- FastSpeech can generate mel-spectrograms with improved robustness and controllability, and can achieve comparable voice quality with previous autoregressive models.
- However, there are still some disadvantages to it:
  1. The two-stage teacher-student distillation pipeline is complicated;
  2. The duration extracted from the attention map of the teacher model is not accurate enough, and the target mel-spectrograms distilled from the teacher model suffer from information loss due to data simplification, both of which limit the voice quality and prosody.
- FastSpeech 2 addresses these issues.
  1. FastSpeech 2 is trained with ground-truth mel targets instead of the simplified output from a teacher.
  2. It uses the Montreal forced alignment tool to extract the phoneme duration.
  3. To reduce the information gap between the input (text sequence) and target output (mel-spectrograms), the input includes pitch, energy, and more accurate duration than the duration of FastSpeech.
     - during training, the duration, pitch, and energy are extracted from the target speech waveform.
     - during inference, these values are predicted by the predictors that were jointly trained with the FastSpeech 2 model.

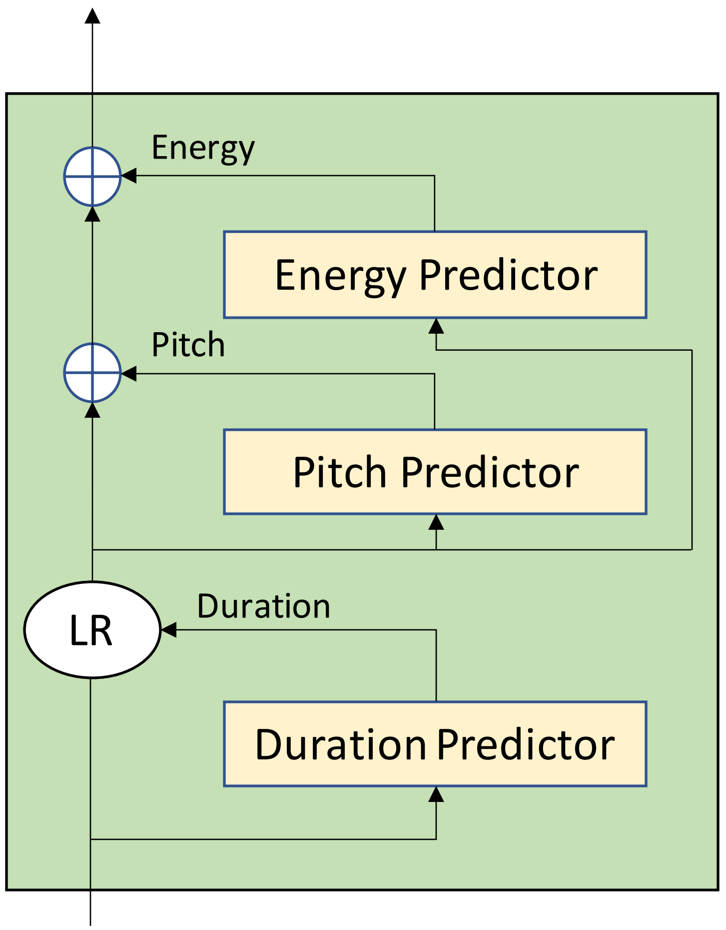
FastSpeech 2



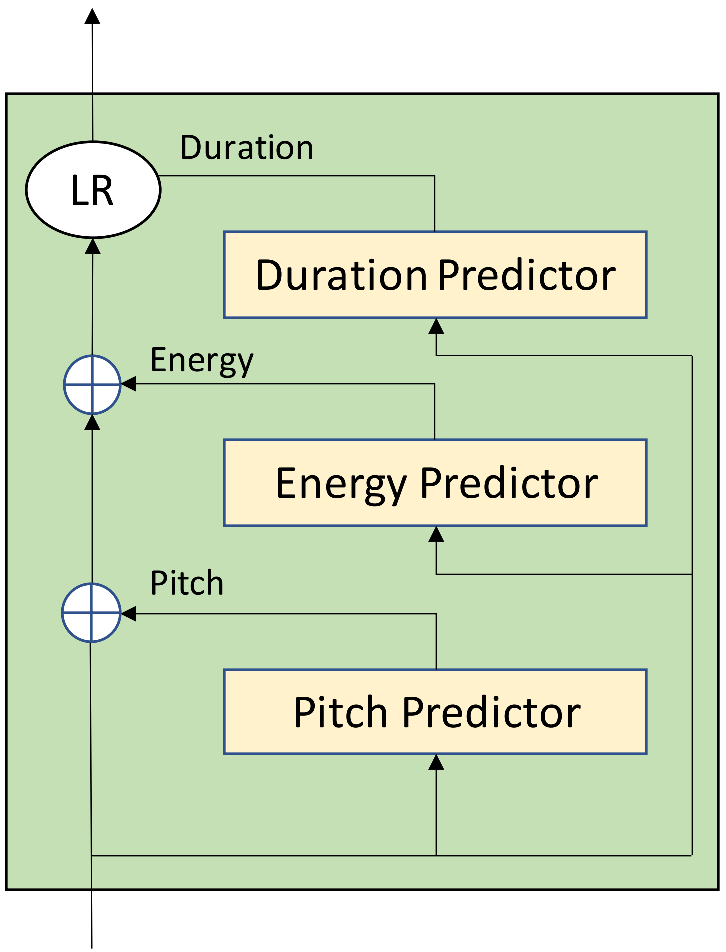
FastSpeech 2



Variance Adaptor



Frame level energy and pitch prediction



Phoneme level energy and pitch prediction

Phoneme level energy and pitch prediction instead of frame level results in better prosody

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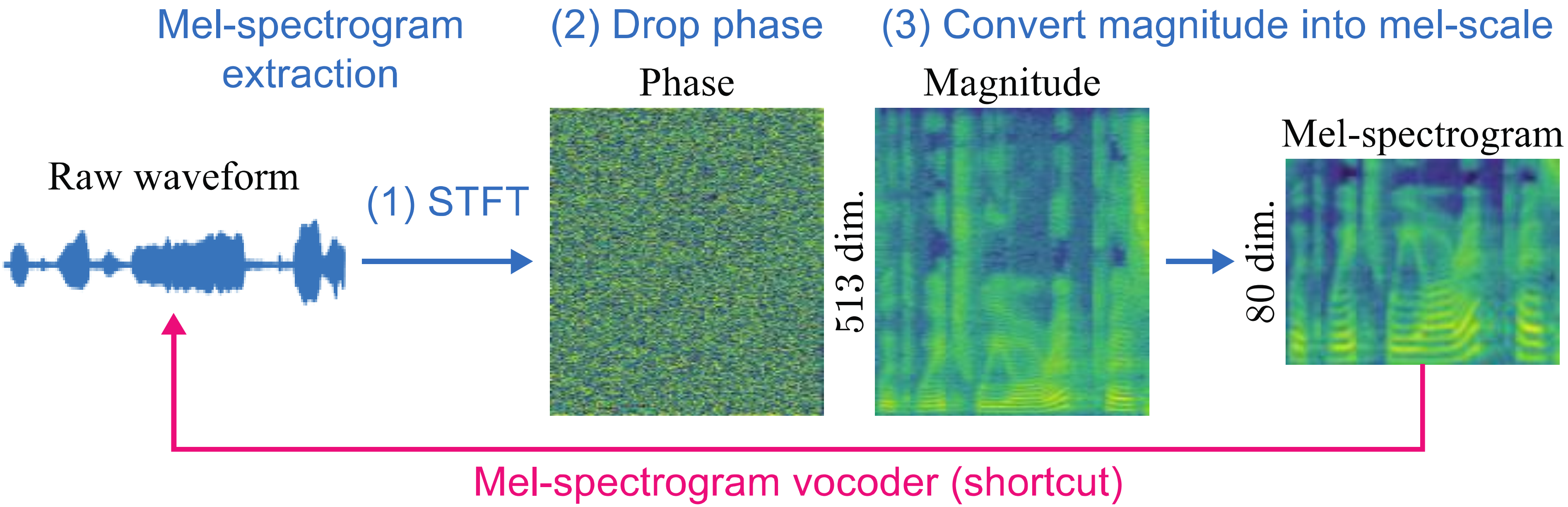
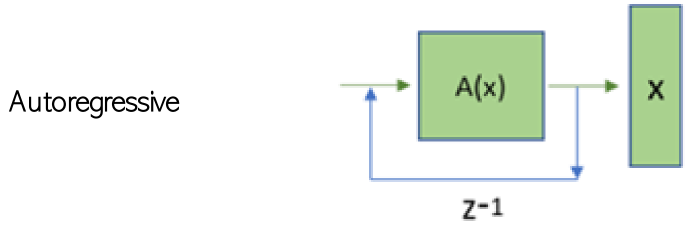
Mel-spectrogram vocoders



Neural Vocoders

- Sequential generation of samples
  - Autoregressive



- Parallel generation of samples
  - GAN-based
  - VAE-based
  - Flow-based
  - Diffusion-based

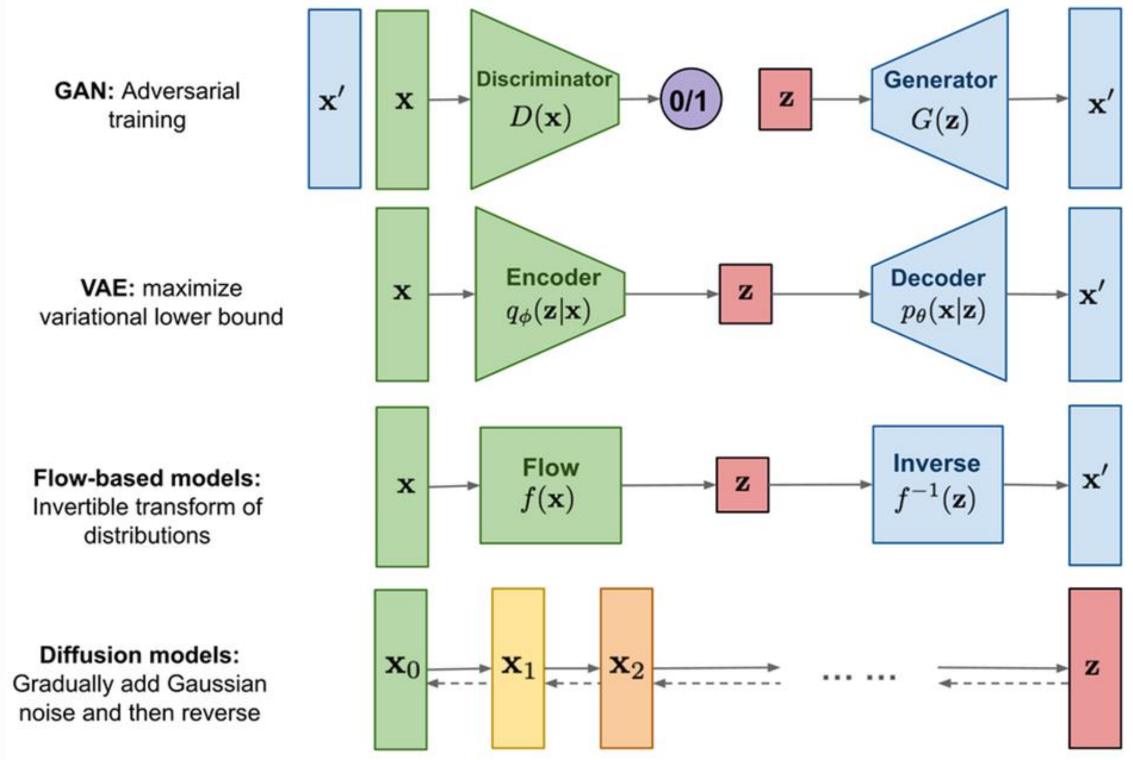
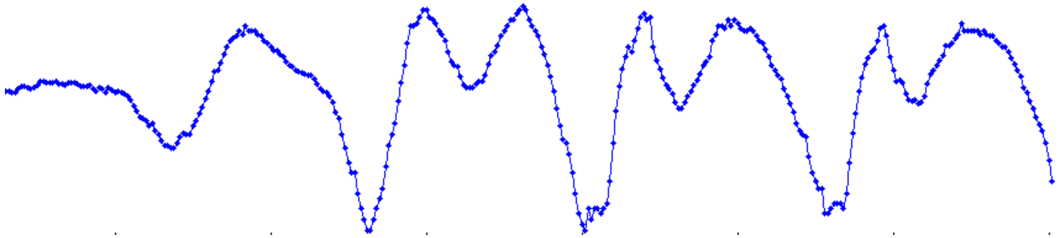


Fig. 1. Overview of different types of generative models.

Autoregressive Neural Vocoders

- Speech: x_0 x_1 x_2 x_3 x_4 ••• x_{T-1}



- The chain rule of probability

$$P(x_0 x_1 x_2 x_3 \ldots x_{T-1}) = P(x_0)\prod_{t=1}^{T-1} P(x_t | x_0 \ldots x_{t-1}) = P(x_0)\prod_{t=1}^{T-1} P(x_t | x_{<t})$$

- Autoregressive neural vocoders model the conditional probability

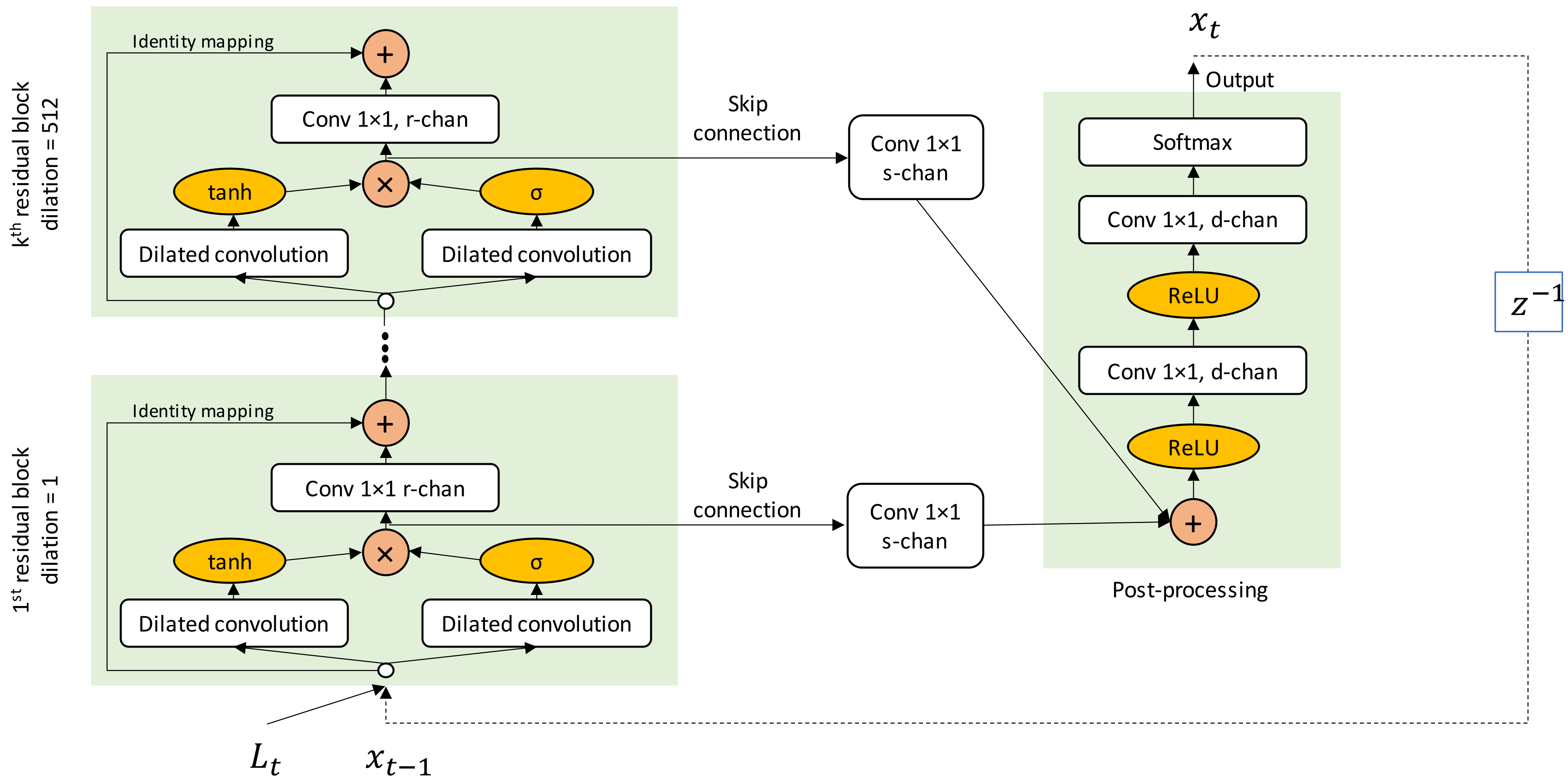
$P(x_t | x_{<t}) \longrightarrow$ Synthesis from this distribution

- And in order to generate speech the conditions include linguistic or acoustic information

$P(x_t | x_{<t}, L_t) \longrightarrow$ Synthesis from this distribution

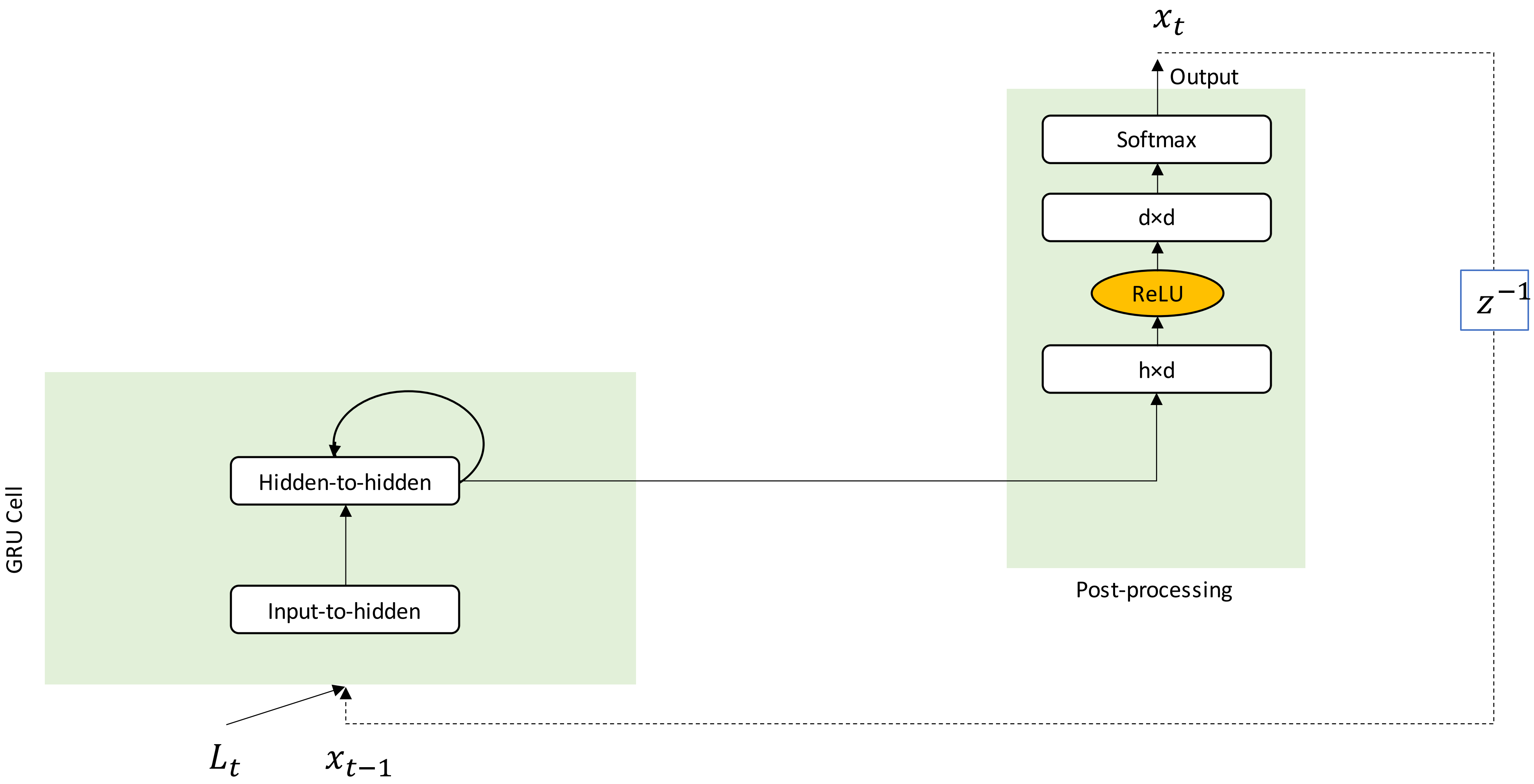
WaveNet

- WaveNets is an autoregressive model, which achieve state-of the art results in audio synthesis.



WaveRNN

- WaveNets achieves state-of the art results in audio synthesis.
- However, sampling from Wavenet is sequential and impractical.
- To increase the efficiency of sampling from these models, Kalchbrenner et al., proposed to substitute the layers of dilated convolutions of WaveNet with a single GRU layer



WaveRNN output

- WaveRNN assigns to an input vector x_t a probability distribution using the softmax function.

$$h(z)_j = \frac{e^{z_j}}{\sum_{c=1}^{256} e^{z_c}}, \quad j = 1, \ldots, 256$$

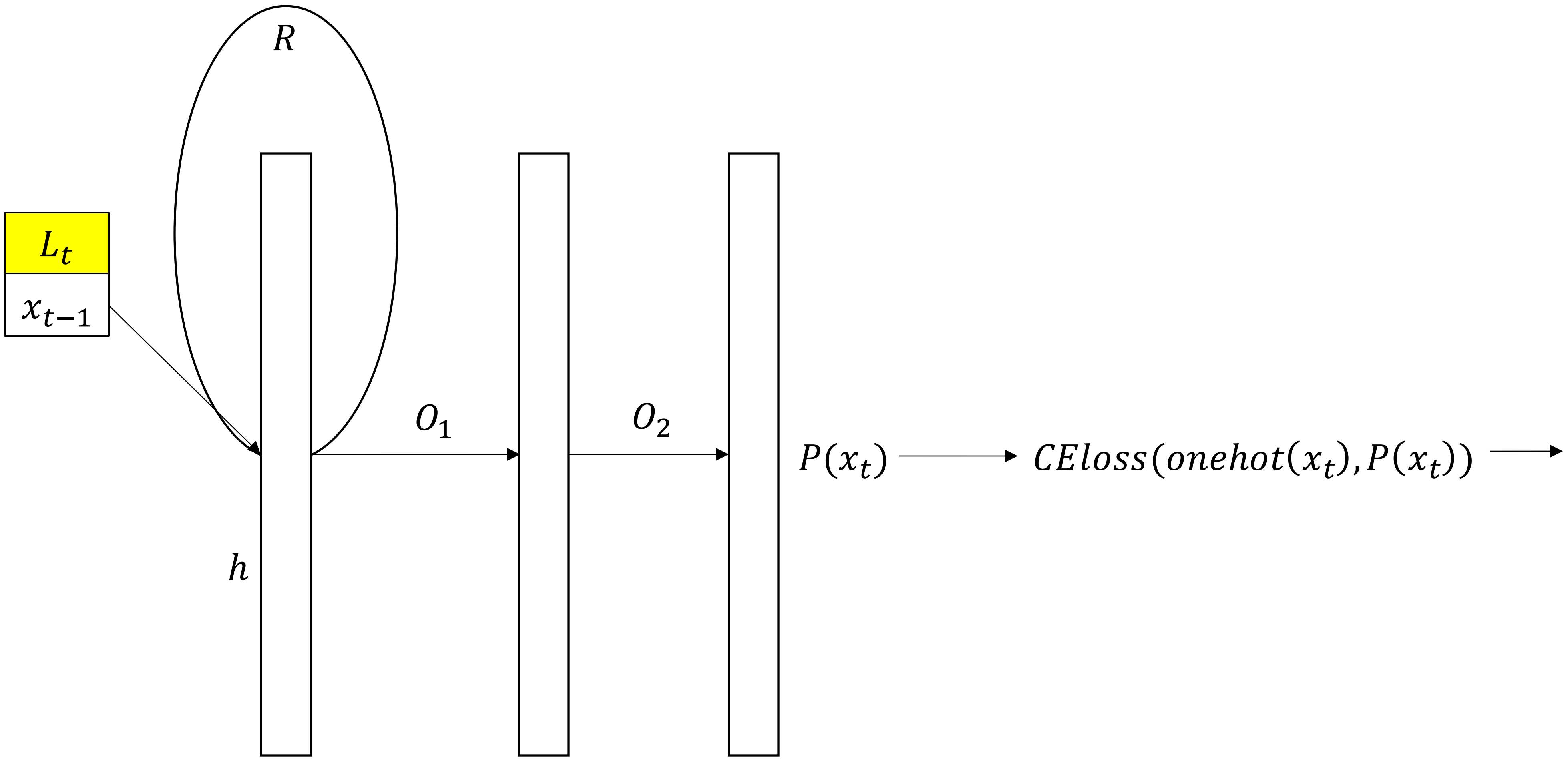
Channels

.6	.2	.1	.1	0
.2	.5	.1	.6	.1
.1	.2	.7	.2	.1
.1	.1	.1	.1	.8

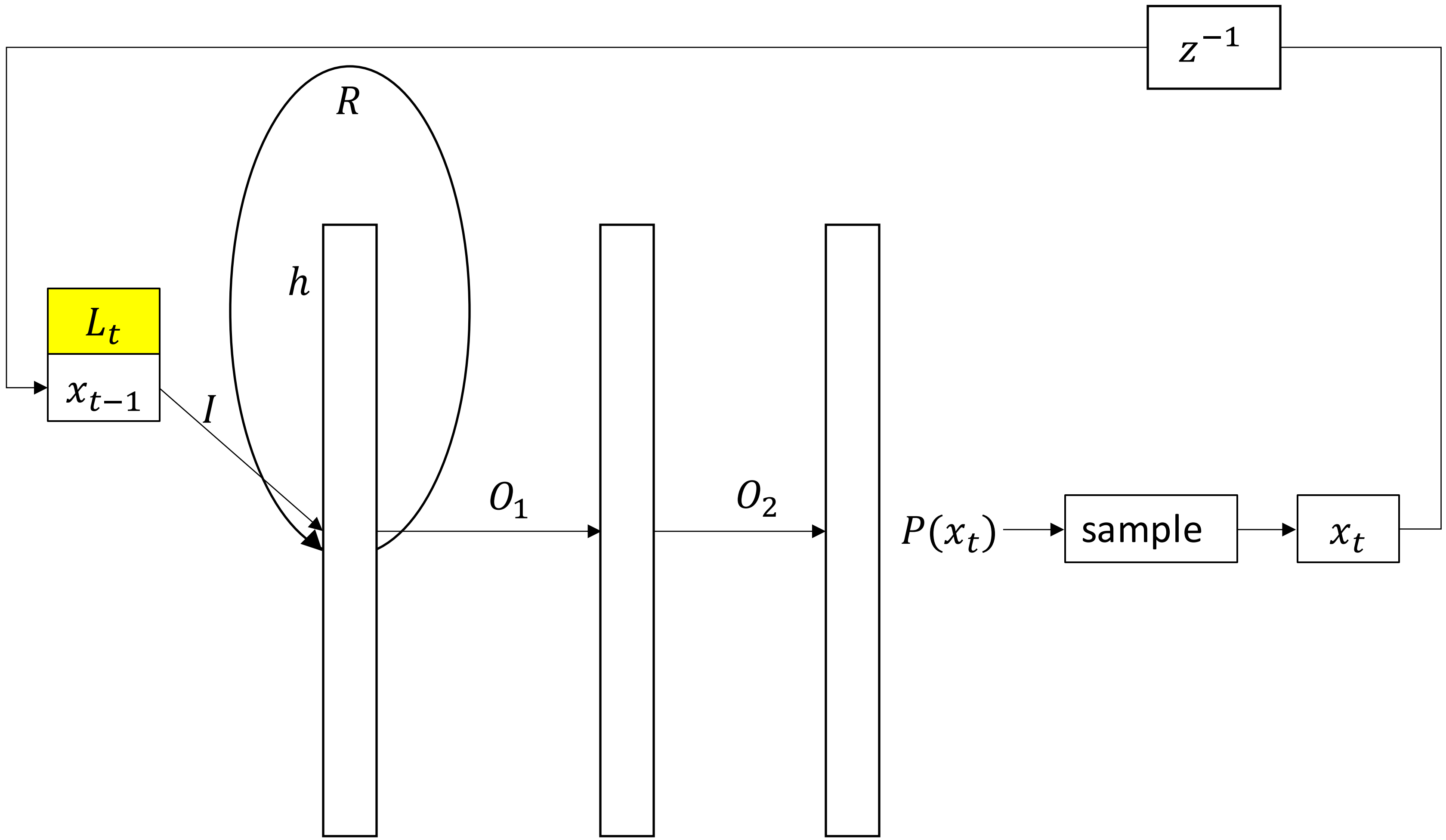
time

WaveRNN output: probabilities from softmax

WaveRNN training



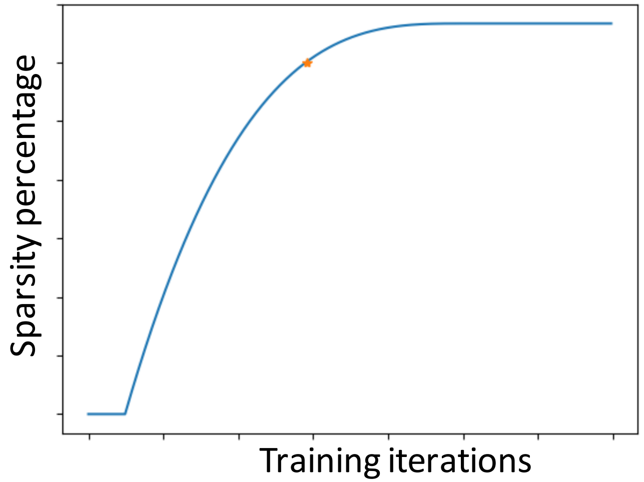
WaveRNN generation

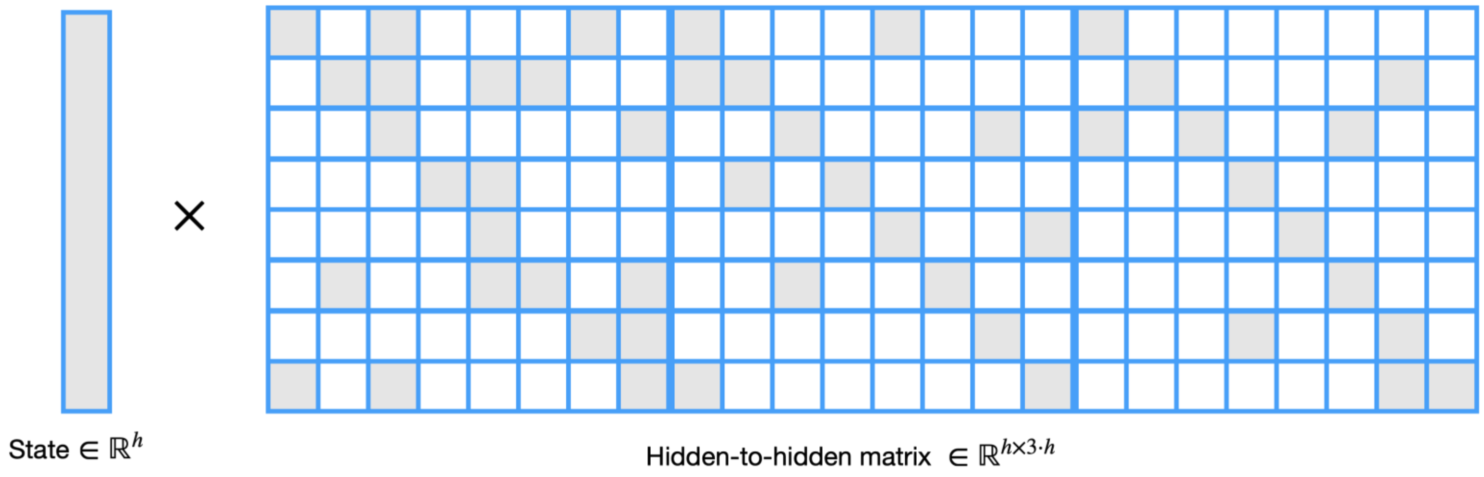


WaveRNN - Samples

Efficient WaveRNN

- Weight pruning
  - Progressively removes the weakest connections.
    1. Randomly initialize a neural network.
    2. Train the network until it converges.
    3. Prune a fraction of the network (the weights with the smallest absolute values).
    4. Repeat steps 2 and 3
  - Use of block or other structured sparsity for efficiency.

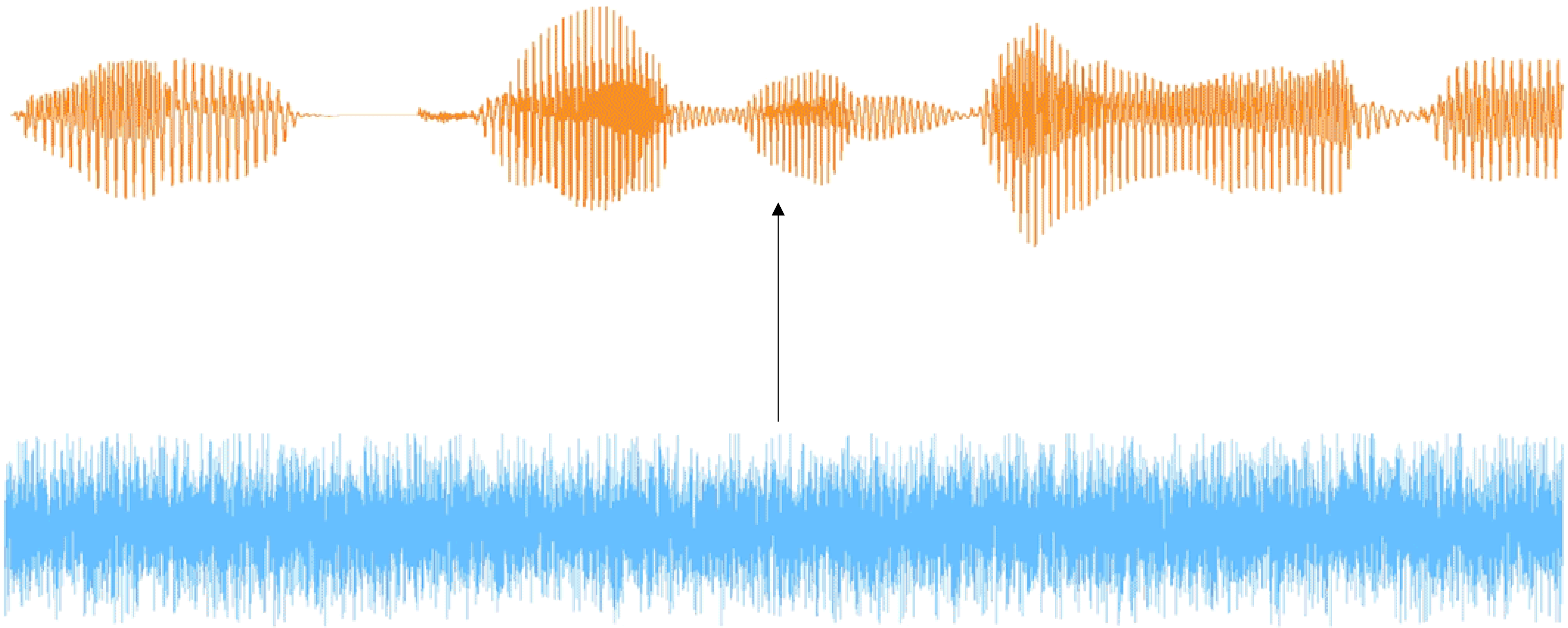




Parallel Vocoders

- During synthesis , parallel vocoders convert noise and conditioning acoustic features to speech.

Speech $x = [x_0, \dots x_{T-1}] \in X$ follows a probability distribution $p_X(x)$



Sample $z = [z_1, \dots, z_T] \in Z$ follows a simple probability distribution $p_Z(z)$.
E.g., samples z_t are independent of each other and they are drawn from a Logistic or a Gaussian distribution.

Samples from Parallel WaveNet

awb_a0001
bdl_a0001
clb_a0001
jmk_a0001
ksp_a0001
rms_a0001
slt_a0001

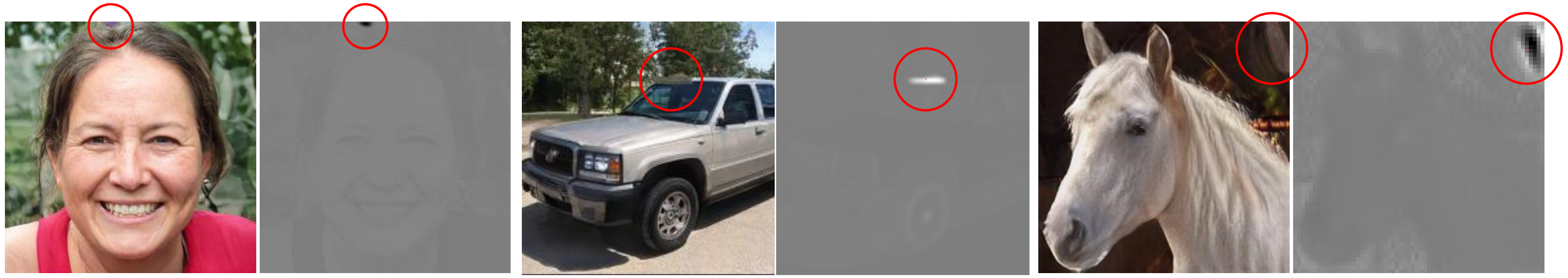
Kullback-Leibler 1/B*powerLoss

awb_a0001
bdl_a0001
clb_a0001
jmk_a0001
ksp_a0001
rms_a0001
slt_a0001

Kullback-Leibler 400/B*powerLoss

Known problems with two stage acoustic models

- Neural network-based TTS systems with two-stage pipelines, usually use mel-scale spectrograms as intermediate representation.
- The neural vocoder is trained separately using ground truth mel spectrograms.
- The distribution of Tacotron or FastSpeech mel-spectrograms differs from the distribution of the ground truth mel-spectrograms.
- This mismatch has no significant effect when the vocoder is autoregressive (WaveNet, WaveRNN).
- However, this mismatch triggers phase artifacts in parallel vocoders.
  - Tested with GAN, flow and diffusion vocoders (MelGAN, HifiGAN, DiffWave, WaveGrad, WaveGlow, WaveFlow).
  - Similar problem in image generation



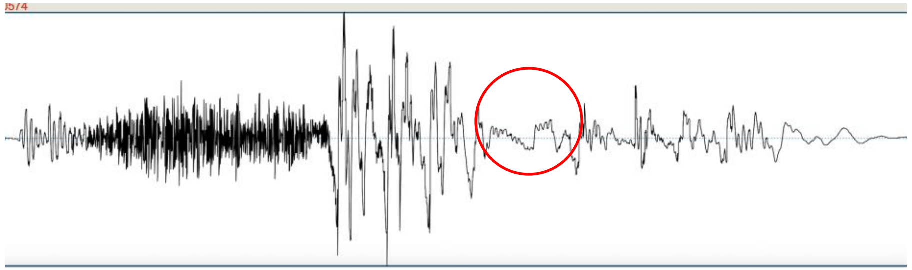
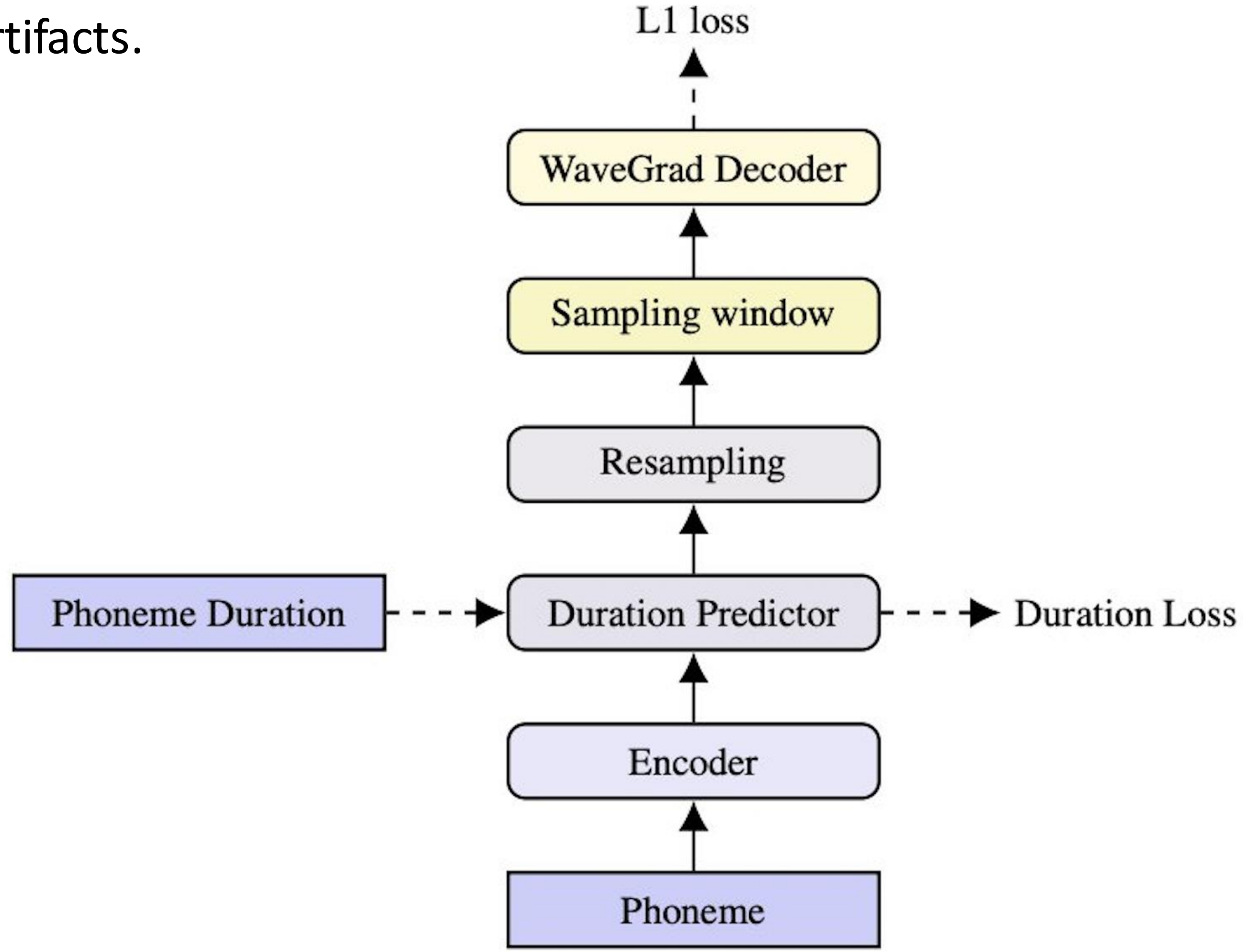


Image taken from Karras et al., Analyzing and Improving the Image Quality of StyleGAN

- Solutions:
  a) Use end-to-end models
  b) Use more robust intermediate representations

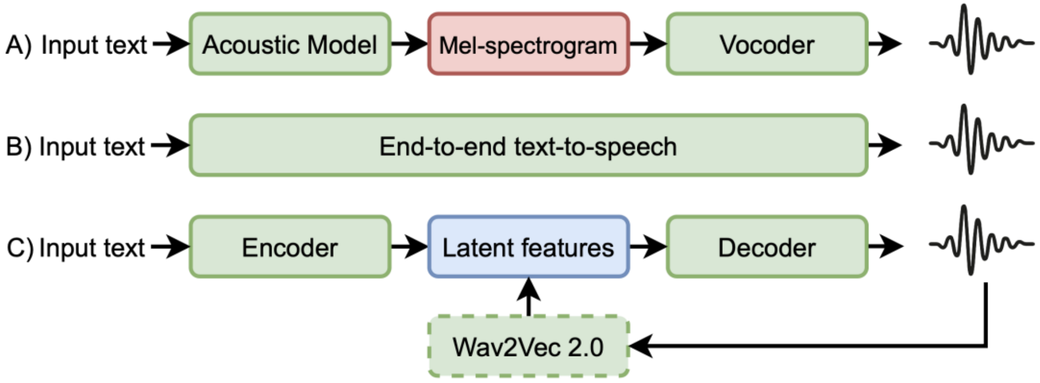
End-to-end systems

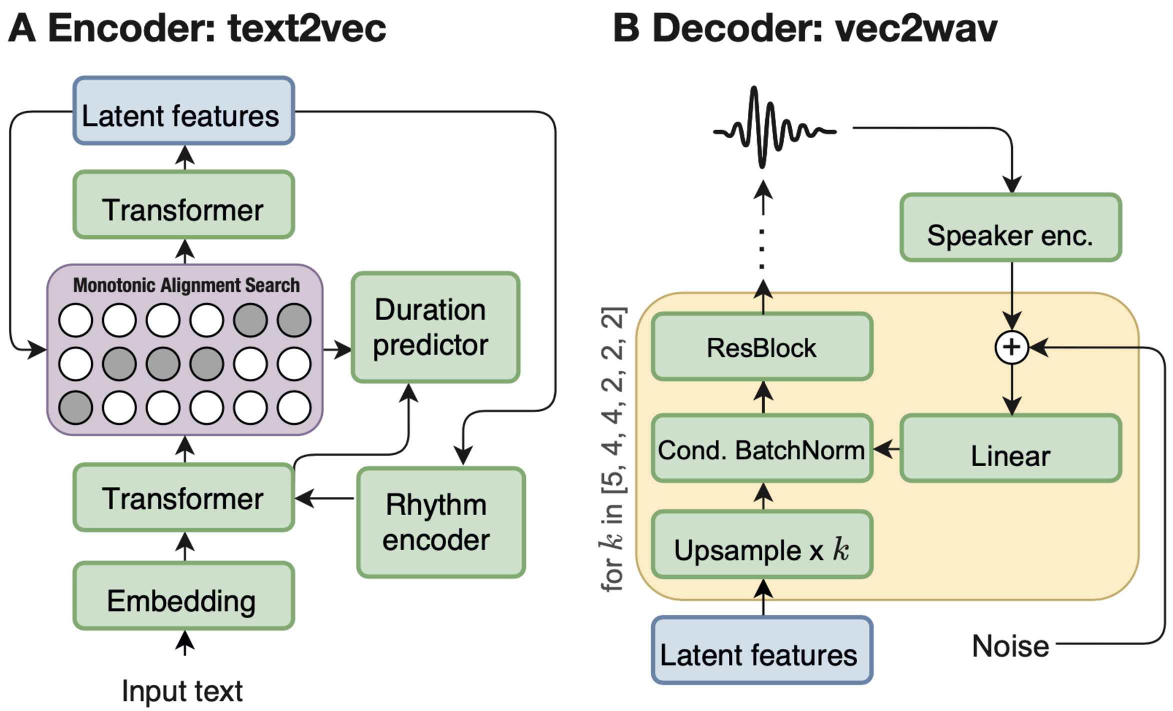
- WaveGrad 2 is a non-autoregressive generative model for text-to-speech synthesis.
- The model takes an input phoneme sequence, and through an iterative refinement process, generates an audio waveform.
- WaveGrad 2 significantly reduces the phase artifacts.



Using high level linguistic features

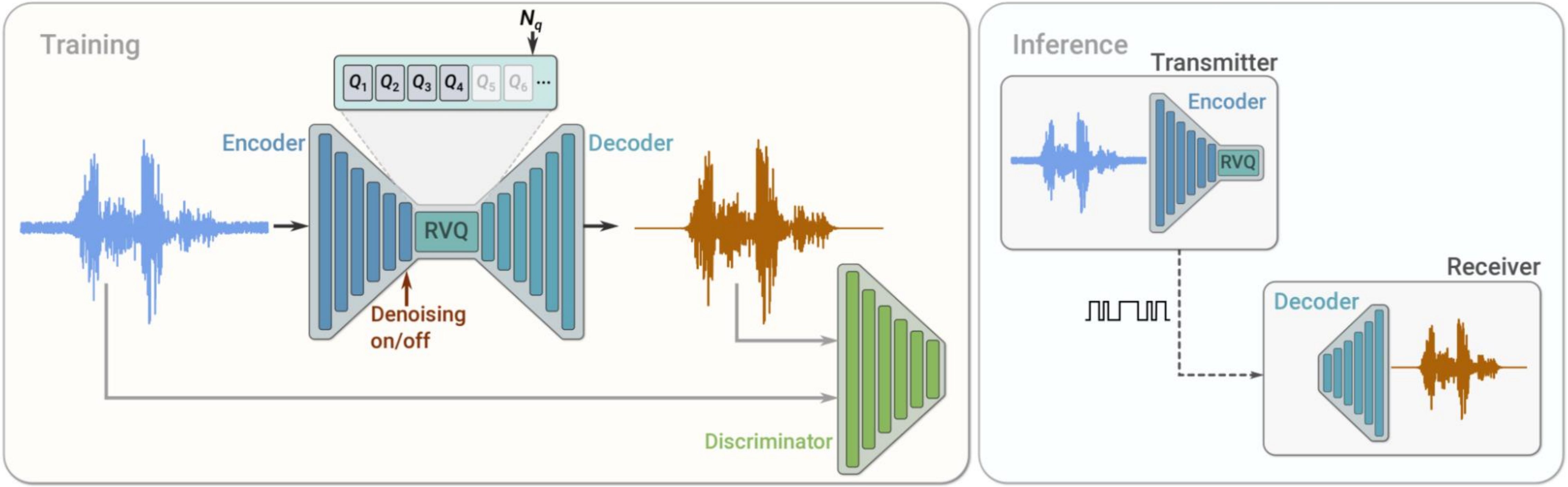
- WavThruVec is a two-stage architecture that uses high-dimensional WAV2VEC 2.0 embeddings as intermediate speech representation.
- Since these hidden activations provide high-level linguistic features, they are more robust to noise.
- Also, their distribution do not change from train to synthesis time.





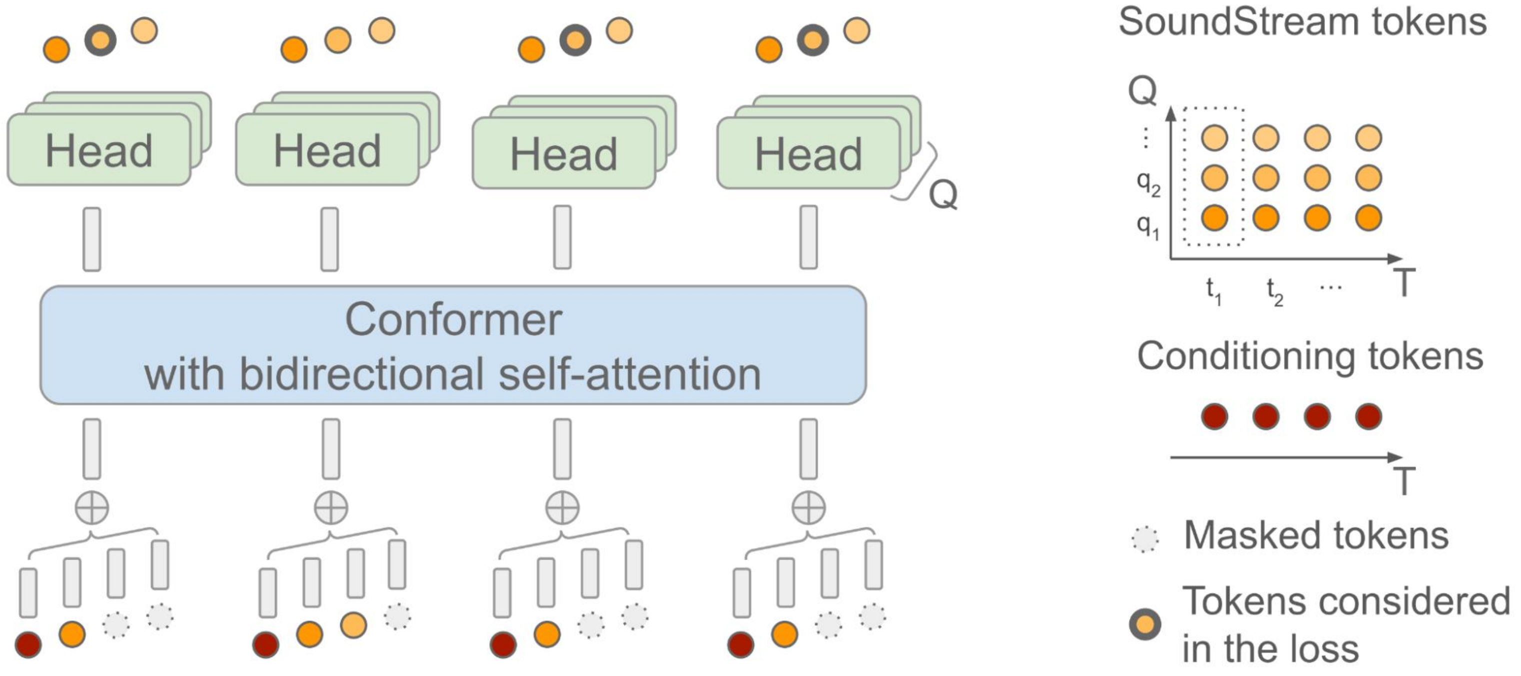
SoundStream: Neural audio codec

- During training, the encoder, quantizer and decoder parameters are optimized using a combination of reconstruction and adversarial losses, computed by a discriminator, which is trained to distinguish between the original input audio and the reconstructed audio.
- During inference, the encoder and quantizer on a transmitter client send the compressed bitstream to a receiver client that can then decode the audio signal.

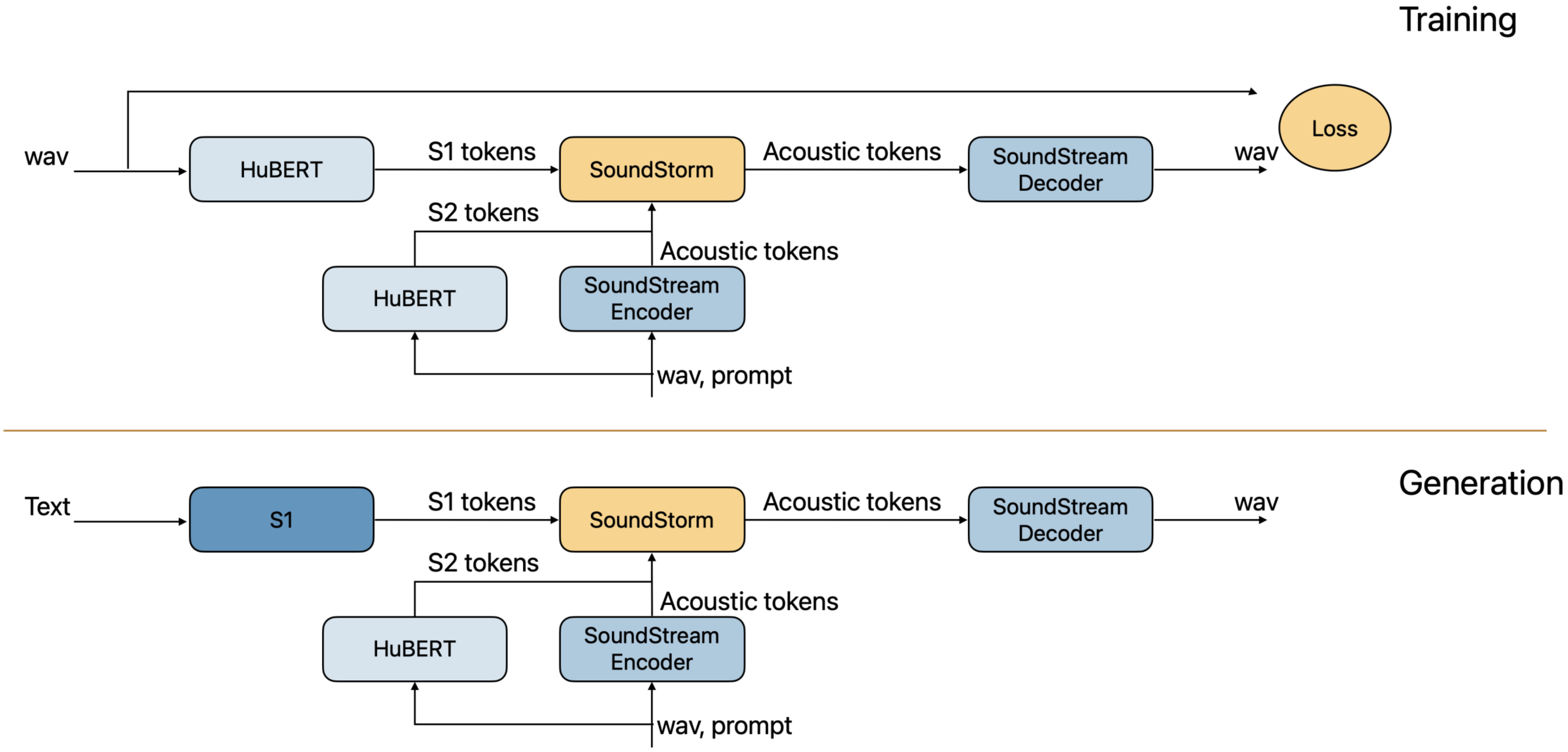


SoundStorm: Efficient parallel audio generation

- Resent generative models often rely on the fact that raw data is first converted to a compressed format as a sequence of tokens.
- In the case of audio, neural audio codecs (e.g., SoundStream) can efficiently compress waveforms to a compact representation, which can be inverted to reconstruct an approximation of the original audio signal.
- Such a representation consists of a sequence of discrete audio tokens, capturing the local properties of sounds (e.g., phonemes) and their temporal structure (e.g., prosody).



Language models for audio generation



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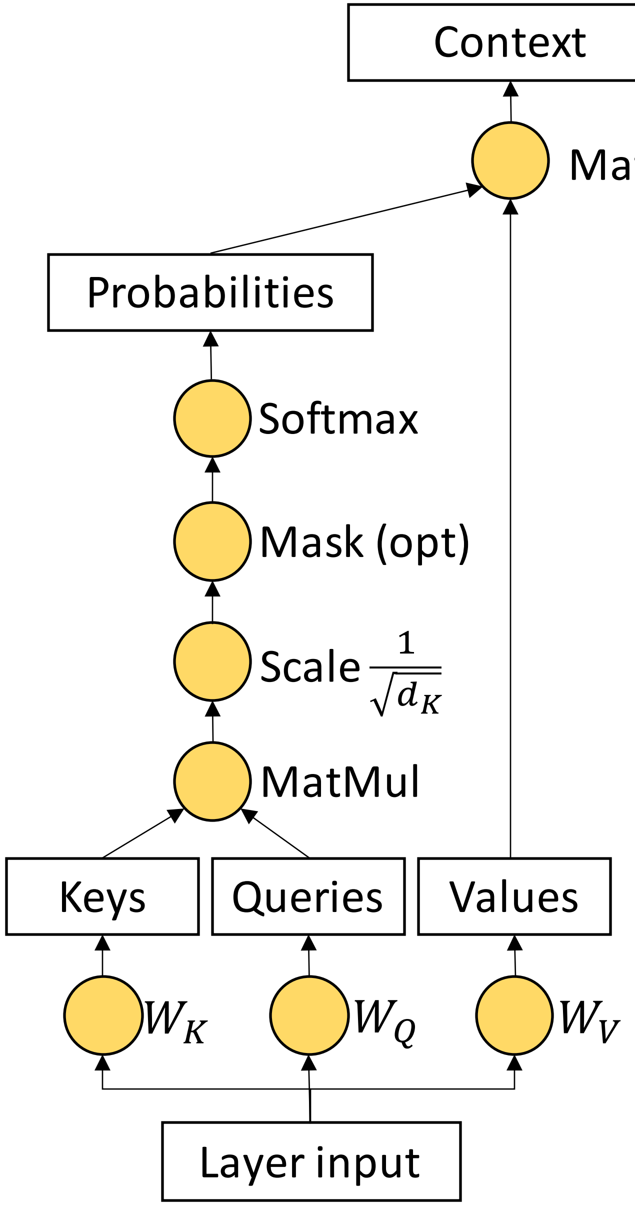
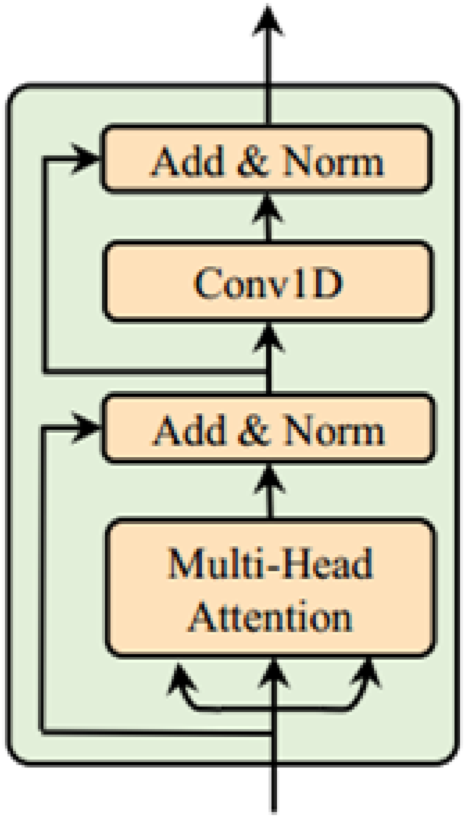
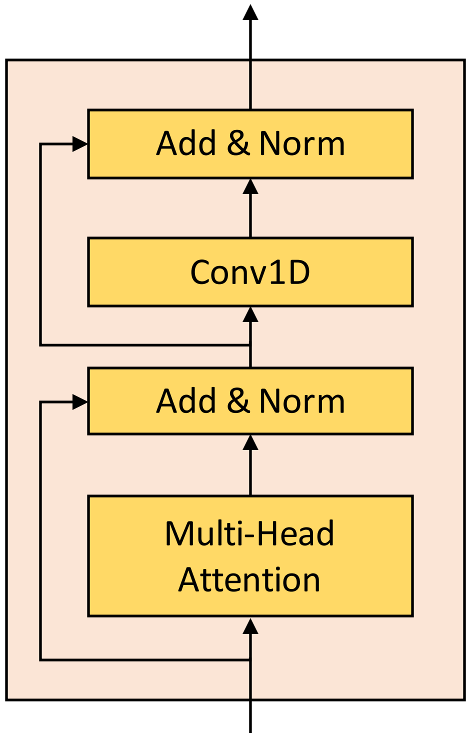
Appendix: The Griffin-Lim algorithm

- The Griffin and Lim's algorithm recovers an audio signal given only the magnitude of its Short-Time Fourier Transform (STFT), also known as the spectrogram.
- It is an iterative algorithm that attempts to find the signal having an STFT such that the magnitude part is as close as possible to the modified spectrogram.
- **Algotithm:**
- Input: s # spectrogram
- $x = random(n\_samples)$ # initialize the reconstructed audio
- for $i = 1: n\_iterations$
    - $c_1 = \mathrm{STFT}(x)$
    - $a = angle(c_1)$
    - $c_2 = s \cdot e^{ja}$
    - $x = \mathrm{ISFTF}(c_2)$ # reconstructed audio
- The Griffin-Lim algorithm converges after 30 to 50 iterations.
- The Griffin-Lim produces characteristic artifacts and lower audio quality than WaveNet.
- Nevertheless, the Griffin-Lim spectrogram inversion is efficient and allows back propagation of derivatives since it is differentiable.
- Therefore, it could be the initial choice when debugging a new end-to-end system.

Scaled Dot-Product Multi-Head Attention







$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$