Neural Speech Synthesis with Transformer Network

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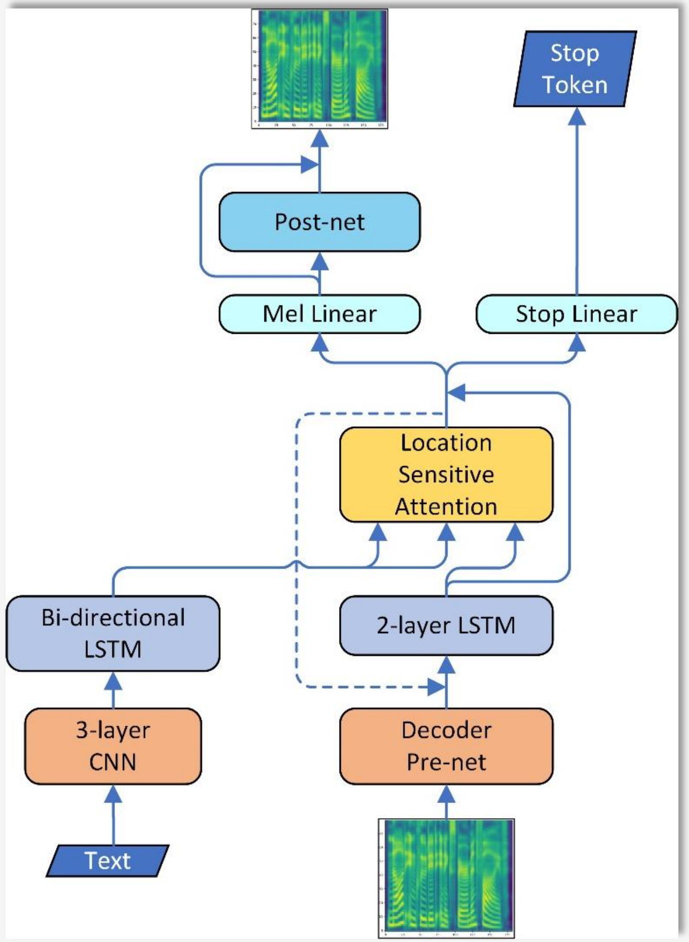
Tacotron2

A neural network architecture for speech synthesis directly from text

- **3-layer CNN**: extracts a longer-term text context.
- **Bi-directional LSTM**: encoder.
- **Location sensitive attention**: connects encoder and decoder.
- **Decoder pre-net**: a 2-layer fully connected network.
- **2-layer LSTM**: decoder.
- **Mel linear**: a fully-connected layer, generates mel spectrogram frames.
- **Stop linear**: a fully-connected layer, predicts the stop token for each frame.
- **Post-net**: a 5-layer CNN with residual connections, refines the mel spectrogram.



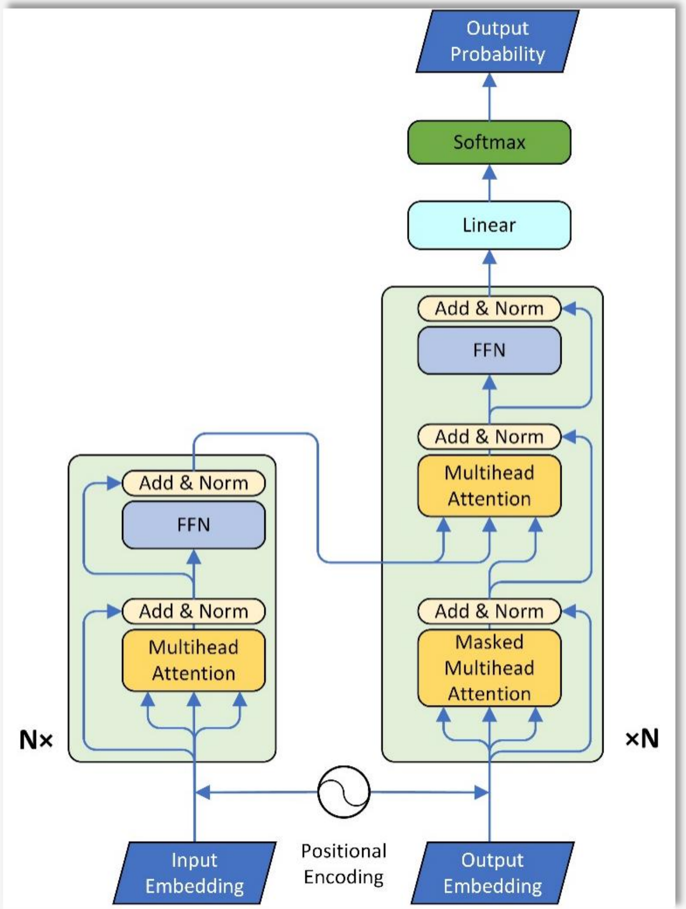
Transformer

A sequence to sequence network based solely on attention mechanisms

- **Encoder:** 6 blocks.
- **Decoder**: 6 blocks.
- **Positional embeddings**: add positional information (PE) to input embeddings

$$PE(pos, 2i) = \sin\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right)$$
$$PE(pos, 2i+1) = \cos\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right)$$

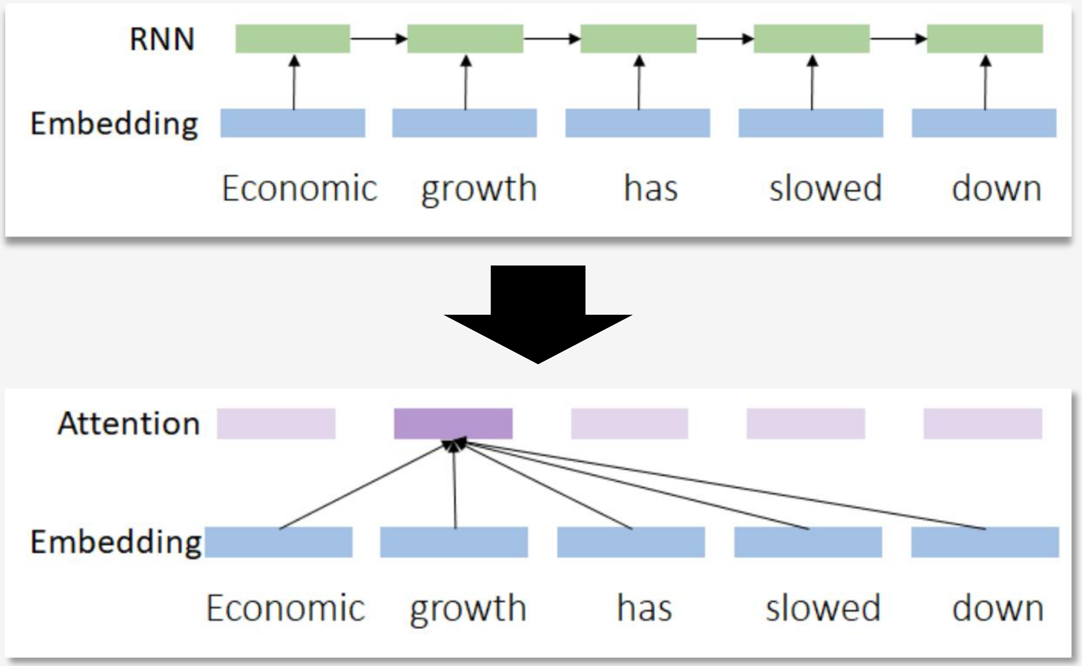
- **(Masked) Multi-head attention**:
  - Splits each Q, K and V into 8 heads
  - Calculates attention contexts respectively
  - Concatenates 8 context vectors
- **FFN**: feed forward network, 2 fully connected layers.
- **Add & Norm**: residual connection and layer normalization.



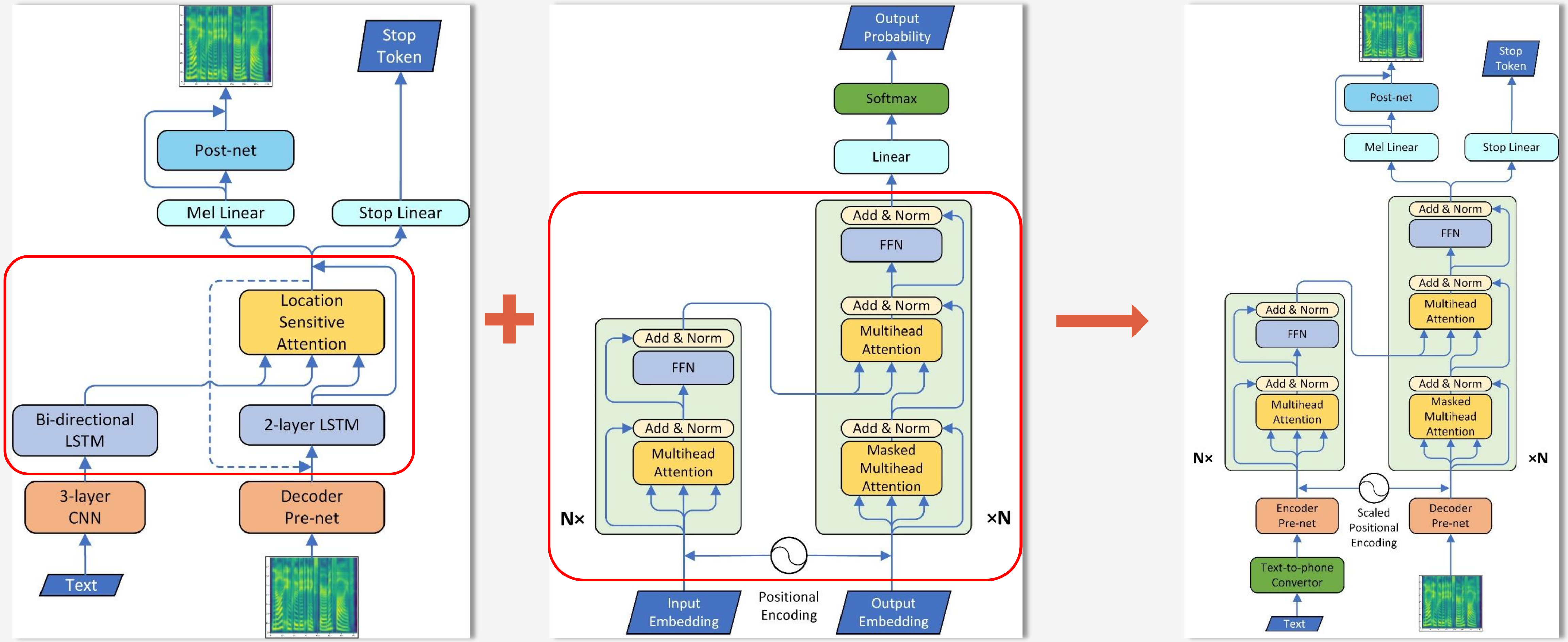
Neural TTS with Transformer

Why apply Transformer in TTS

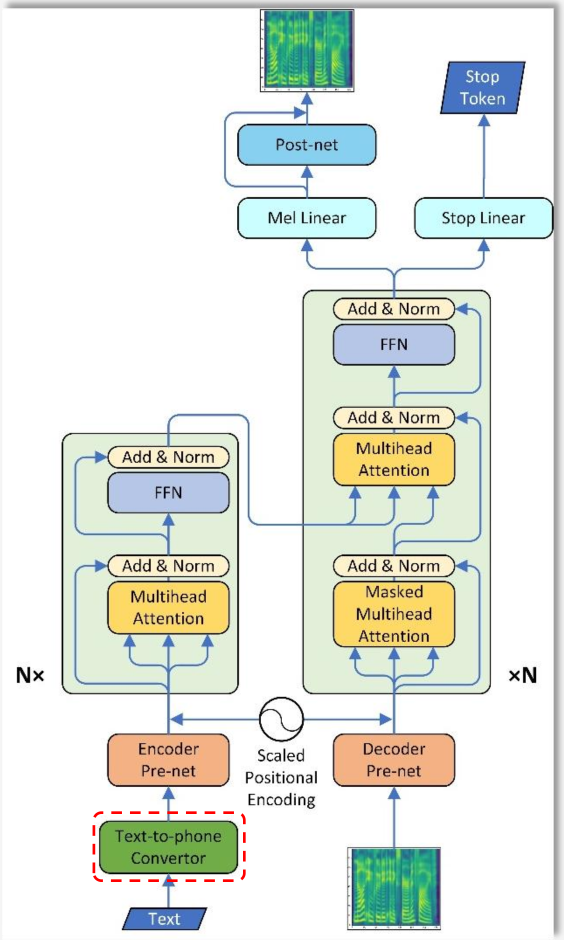
- **Parallel training**
  Frames of an input sequence can be provided in parallel.
- **Long range dependencies**
  Self attention injects global context of the whole sequence into each input frame.



Neural TTS with Transformer

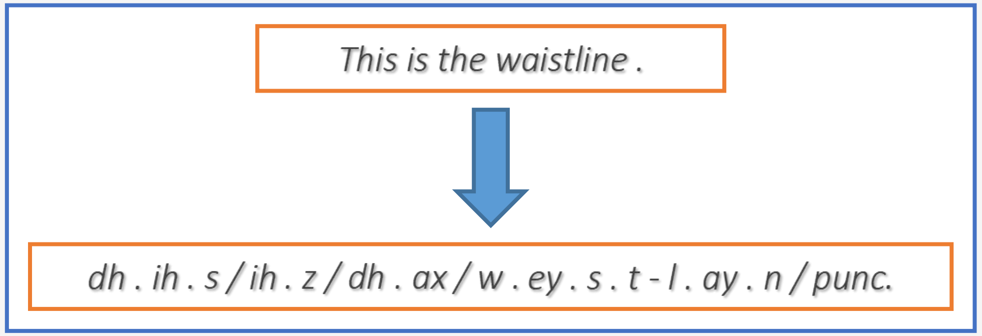


Neural TTS with Transformer

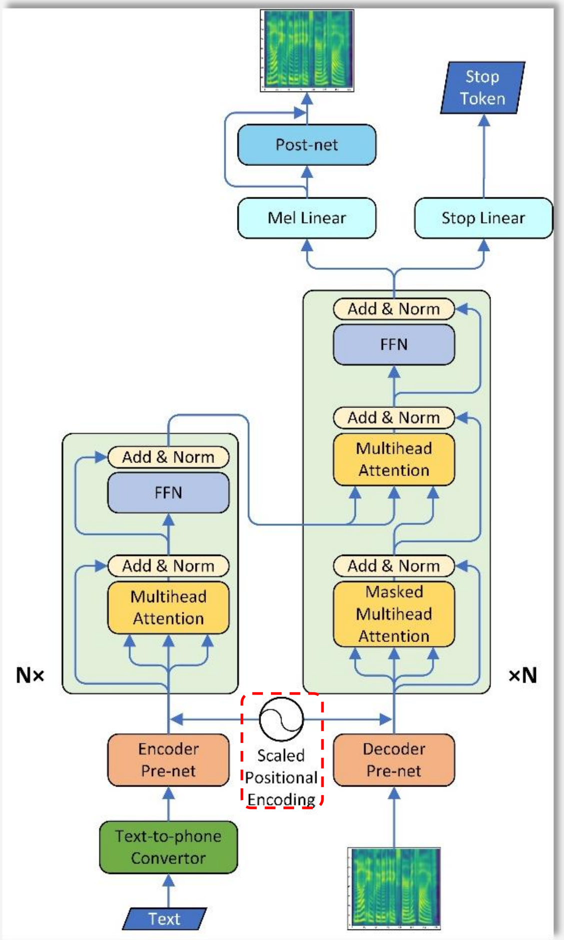


Text-to-Phoneme Converter

- Difficult to learn all the regularities without sufficient training data
- Some exceptions have too few occurrences for neural networks to learn
- Convert text into phonemes by rule:



Neural TTS with Transformer



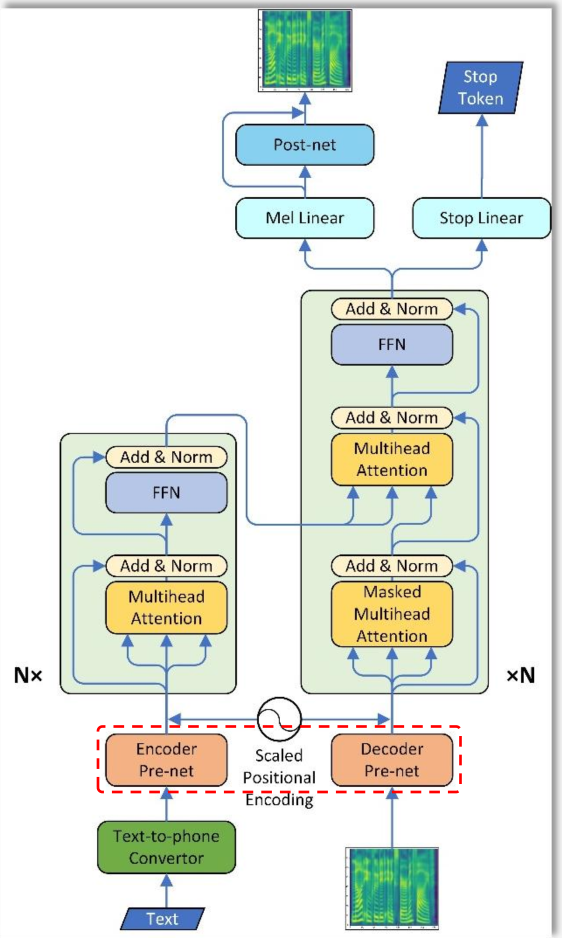
Scaled Positional Encoding

- Transformer adds information about the relative or absolute position by adding a positional embedding (PE) to input embeddings
- In TTS scenario, texts and mel spectrograms may have different scales
  - Scale-fixed positional embeddings may impose heavy constraints on both the encoder and decoder pre-nets
- Add a trainable weight to positional embeddings

$$x_i = prenet(phoneme_i) + \alpha \cdot PE(i)$$

  - Positional embeddings can adaptively fit the scales of both encoder and decoder pre-nets' output

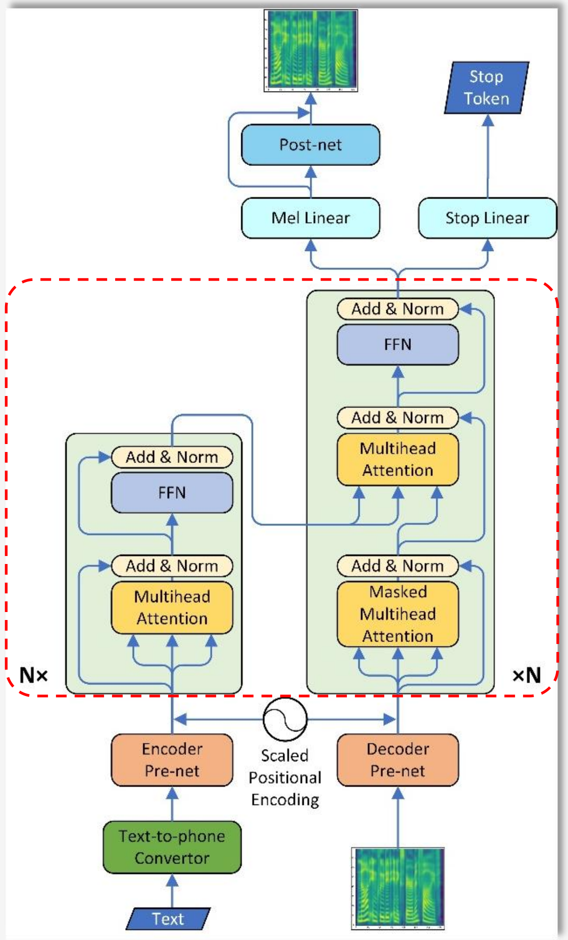
Neural TTS with Transformer



Pre-nets of Encoder and decoder

- Similar structure and function as in Tacotron2
- An additional linear projection is appended
  - Positional embeddings are in $[-1, 1]$
  - After *relu*, the outputs of pre-nets are in $[0, +\infty)$
  - Re-center to have a 0-centered range

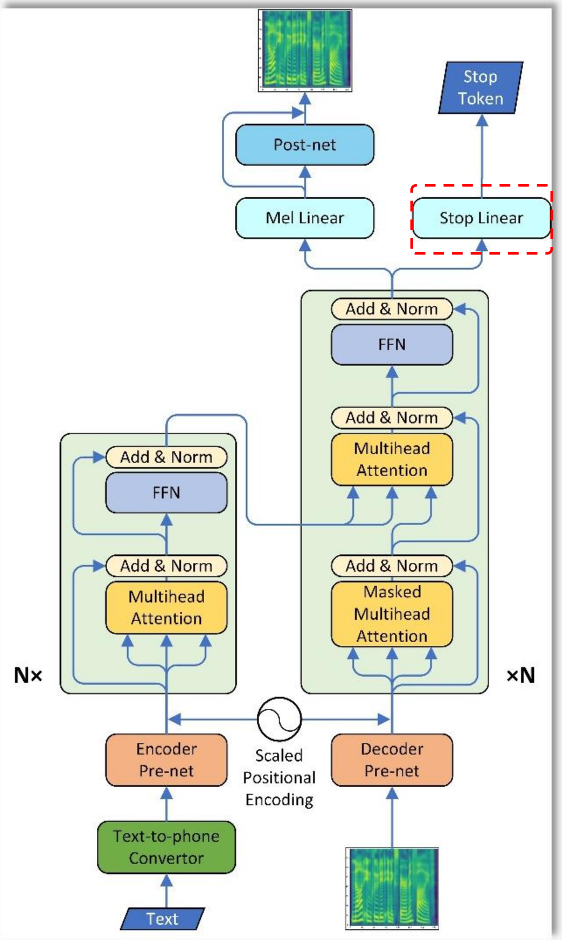
Neural TTS with Transformer



Encoder and decoder

- Model the frame relationship in multiple different aspects.
- Inject the global context of the whole sequence into each frames.
- Enable parallel computing to improve training speed.

Neural TTS with Transformer



Stop linear

- Predicts whether should inference stop at current frame.
- Unstoppable inference may occur
  - During training, each sequence has only one "stop" while hundreds of “continue”.
  - Imbalance positive/negative samples result in biased stop linear.
  - Solution: impose a weight (5.0 ~ 8.0) on the "stop" token when calculating binary cross entropy loss during training.

Experiment

Training Setup

- 4 Nvidia Tesla P100
- Internal US English female dataset
  - 25-hour professional speech
  - 17584 text-wave pairs
- Dynamic batch size
  - Various sample number
  - Fixed mel spectrogram frame number

Text-to-Phoneme Conversion and Pre-process

- Phoneme type:
  - Normal phonemes
  - Word boundaries
  - Syllable boundaries
  - Punctuations
- Process pipeline:
  - Sentence separation
  - Text normalization
  - Word segmentation
  - Obtaining pronunciation

WaveNet Settings

- Sample rate: 16000
- Frame rate (frames per second): 80
- 2 QRNN layers
- 20 dilated layers
- Residual and dilation channel size: 256

Experiment

Training Time Comparison

	Tacotron2	Transformer
Single step (batch size=~16)	~ 1.7s	~ 0.4s
Total time	~4.5 days	~3 days

Inference Time Comparison

	Tacotron2	Transformer
Synthesize 1s spectrogram	~ 0.13s	~ 0.36s

Evaluation

Evaluation setup

- 38 fixed examples with various lengths
- Each audio is listened to by at least 20 testers (8 testers Shen et al. (2017))
- Each tester listens less than 30 audios

Baseline model

- Tacotron2
  - Use phone sequence as inputs
  - Other structure are same as Google's version

Results

System	MOS	CMOS
Tacotron2	4.39 ± 0.05	0
Our Model	4.39 ± 0.05	**0.048**
Ground Truth	4.44 ± 0.05	-

CMOS: comparison mean option score. Testers listen to two audios each time and evaluates how the latter feels comparing to the former using a score in [−3, 3] with intervals of 1

Evaluation

Generated sample comparison

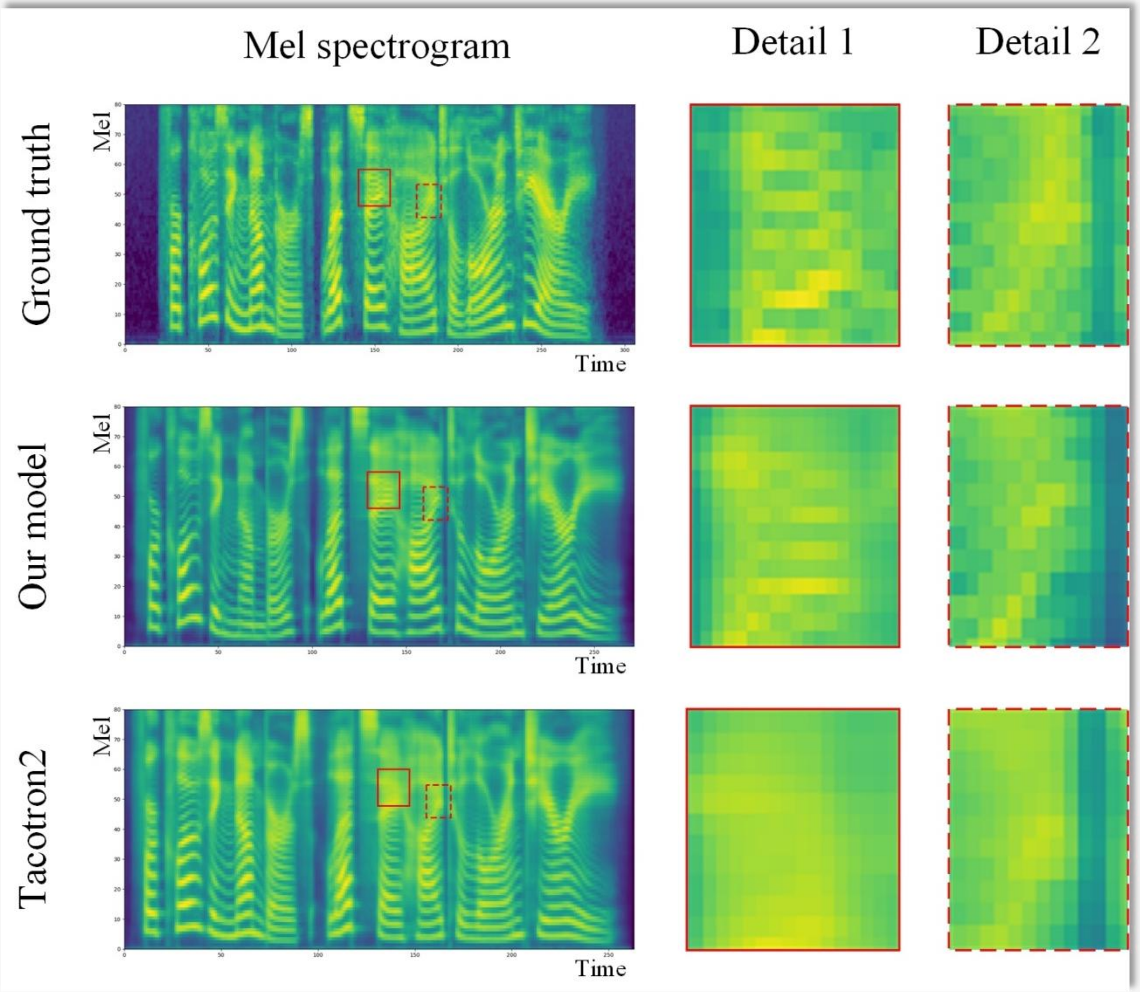
Our model			
Tacotron2			

More samples at https://neuraltts.github.io/transformertts/

Evaluation

Mel spectrogram details

- Our model does better in reproducing high frequency region



Ablation Studies

Re-centering Pre-net’s Output

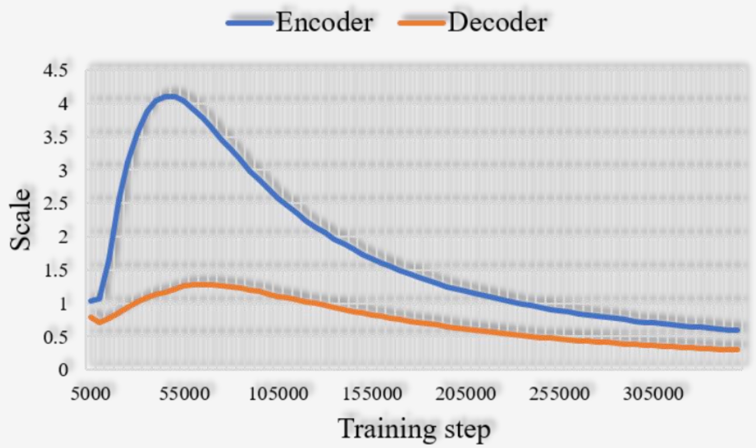
- Re-project pre-nets’ outputs for consistent center with positional embeddings
- Center-consistent PE performs slightly better

Re-projection	MOS
No	4.32 ± 0.05
Yes	$\mathbf{4.36} \pm 0.05$
Ground Truth	4.43 ± 0.05

Ablation Studies

Different Positional Encoding Methods

- Final positional embedding scales of encoder and decoder are different
- Trainable scale performs slightly better.
- Reason:
  - Constraint on encoder and decoder pre-nets are relaxes
  - Positional information are more adaptive for different embedding spaces

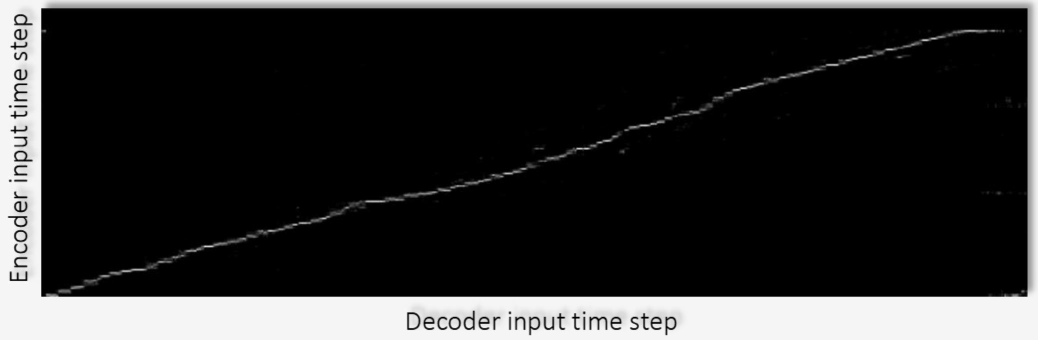


PE Type	MOS
Original	4.37 ± 0.05
Scaled	$\mathbf{4.40} \pm 0.05$
Ground Truth	4.41 ± 0.04

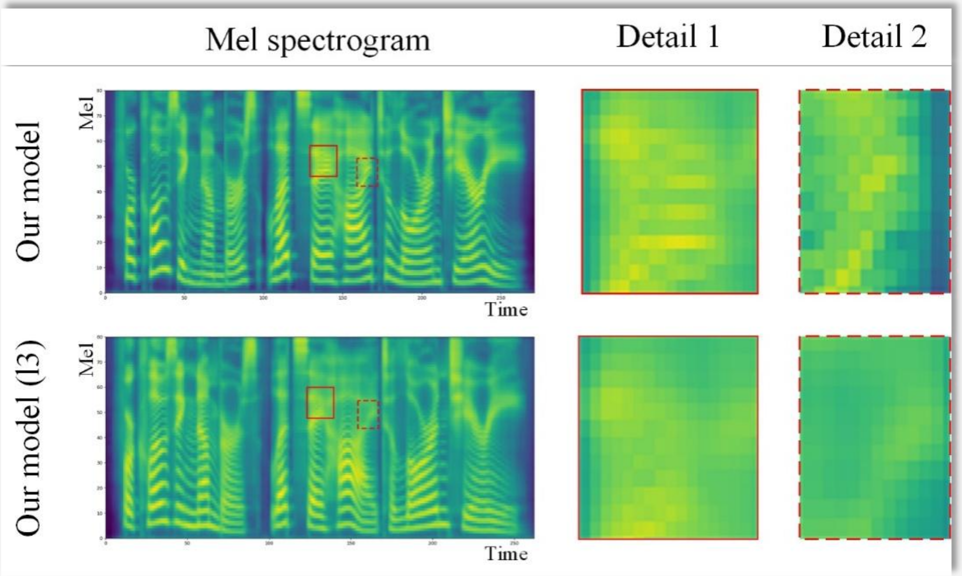
Ablation Studies

**Different Hyper-Parameter:
layer number impact**

- For encoder-decoder attention, only alignments from certain heads of the beginning 2 layers' are interpretable diagonal lines



- More layers can still refine the synthesized mel spectrogram and improve audio quality



Ablation Studies

Different Hyper-Parameter:
head number impact

- Reducing head numbers harms performance

Head Number	MOS
4-head	4.39 ± 0.05
8-head	$\mathbf{4.44} \pm 0.05$
Ground Truth	4.47 ± 0.05

- Comparison of time consuming (in second) per training step of different layer and head numbers

	3-layer	6-layer
4-head	-	0.44
8-head	0.29	0.50

(Tested on 4 GPUs with dynamic batch size)

Thank you!