

Tacotron 2

Natural TTS synthesis by conditioning WaveNet on Mel
Spectrogram predictions

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Overview

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- History of speech synthesis

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 - Gated activation

 - Residual and skip connections

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Tacotron 2

- Architecture

- Training

- Evaluation

- Reported results

Conclusions and future strategies

Speech synthesis

Artificial production of human speech

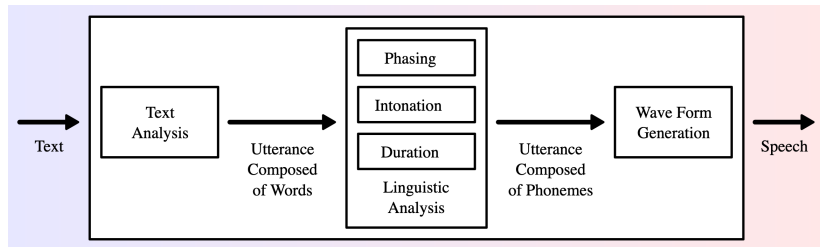


Figure: A typical text-to-speech system¹

¹Andy0101, *A typical text-to-speech system*, https://commons.wikimedia.org/wiki/File:TTS_System.svg, [Online; accessed 10/08/2019], 2010.

History of speech synthesis²

Concatenative

- ▶ Extract samples from large database of human speech

Parametric

- ▶ Simulate human voice using a parametric function

Neural

- ▶ Artificially generate human voice using neural networks

²V. Delić, Z. Perić, M. Sečujski, *et al.*, "Speech Technology Progress Based on New Machine Learning Paradigm," en, *Computational Intelligence and Neuroscience*, vol. 2019, pp. 1–19, Jun. 2019, ISSN: 1687-5265, 1687-5273. DOI: 10.1155/2019/4368036. [Online]. Available: <https://www.hindawi.com/journals/cin/2019/4368036/> (visited on 10/08/2019).

WaveNet

A deep neural network for generating raw audio waveforms.

- ▶ Probabilistic
- ▶ Autoregressive
- ▶ Beats all previously known methods



Figure: Time domain representation of 1 second of generated speech³

³D. Blog, *WaveNet: A generative model for raw audio*,
<https://deepmind.com/blog/article/wavenet-generative-model-raw-audio>, [Online; accessed 10/08/2019], 2016.

WaveNet: Architecture

Important Components

- ▶ Dilated convolution
- ▶ μ law companding
- ▶ Gated activation
- ▶ Residual and skip connection
- ▶ Conditional wavenets

1. Conditional WaveNets

Given an additional input \mathbf{h} , WaveNets can model the conditional distribution $p(\mathbf{x}|\mathbf{h})$ of the audio given the input,

$$p(\mathbf{x}|\mathbf{h}) = \prod_{t=1}^T p(x_t|x_1, \dots, x_{t-1}, \mathbf{h})$$

2. Dilated Causal Convolution

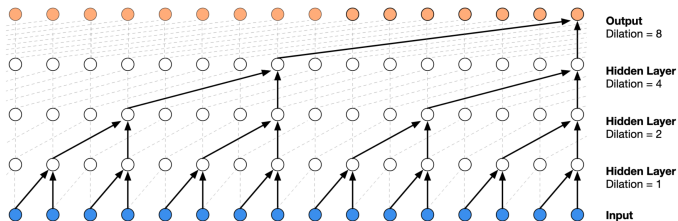


Figure: Stack of dilated causal convolution layers⁴

⁴A. v. d. Oord, S. Dieleman, H. Zen, *et al.*, "WaveNet: A Generative Model for Raw Audio," *en, arXiv:1609.03499 [cs]*, Sep. 2016, arXiv: 1609.03499. [Online]. Available: <http://arxiv.org/abs/1609.03499> (visited on 10/08/2019).

3. μ -law companding⁵

$$f(x_t) = \text{sign}(x_t) \frac{\ln(1 + \mu|x_t|)}{\ln(1 + \mu)}$$

$-1 < x_t < 1$ is the time domain speech signal,
 $\mu = 255$

⁵Cisco, *Waveform coding techniques*,

<https://www.cisco.com/c/en/us/support/docs/voice/h323/8123-waveform-coding.html>, [Online; accessed 10/09/2019], 2008.

4. Gated activation⁶

$$\mathbf{z} = \tanh(W_{f,k} * \mathbf{x}) \circledast \sigma(W_{g,k} * \mathbf{x})$$

$*$ \rightarrow convolution,

\circledast \rightarrow element-wise multiplication,

$\sigma(\cdot)$ \rightarrow sigmoid function,

k \rightarrow layer index,

f \rightarrow filter,

g \rightarrow gate,

W \rightarrow learnable convolution filter

⁶A. v. d. Oord, N. Kalchbrenner, O. Vinyals, *et al.*, “Conditional Image Generation with PixelCNN Decoders,” *arXiv:1606.05328 [cs]*, Jun. 2016, arXiv: 1606.05328. [Online]. Available: <http://arxiv.org/abs/1606.05328> (visited on 10/08/2019).

5. Residual and skip connections

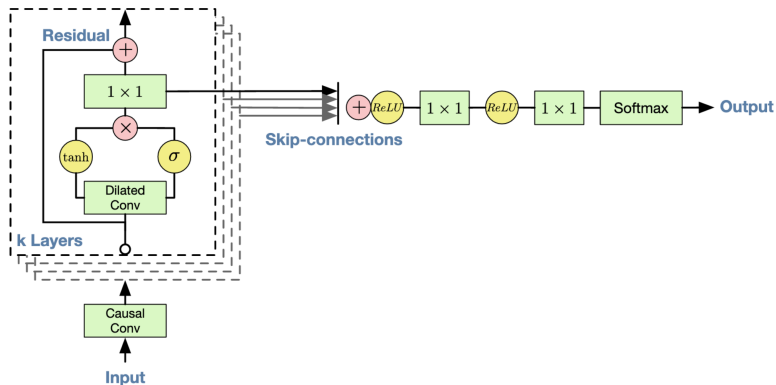


Figure: Overview of residual block and entire architecture⁷

⁷A. v. d. Oord, S. Dieleman, H. Zen, *et al.*, "WaveNet: A Generative Model for Raw Audio," *en, arXiv:1609.03499 [cs]*, Sep. 2016, arXiv: 1609.03499. [Online]. Available: <http://arxiv.org/abs/1609.03499> (visited on 10/08/2019).

WaveNet: Reported results

Reported results

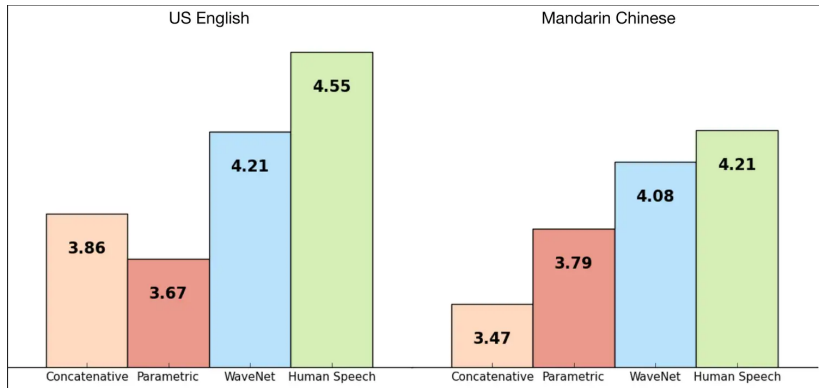


Figure: Mean Opinion Scores (MOS) for English and Mandarin⁸

⁸D. Blog, *WaveNet: A generative model for raw audio*, <https://deepmind.com/blog/article/wavenet-generative-model-raw-audio>, [Online; accessed 10/08/2019], 2016.

Tacotron 2: Architecture

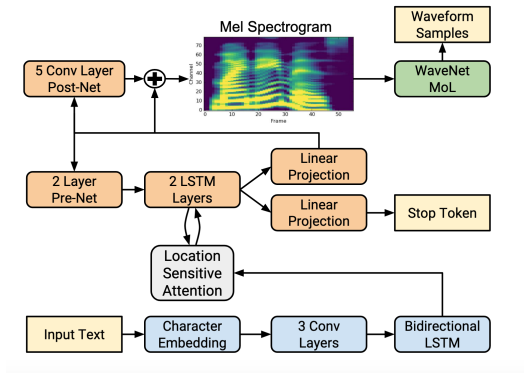


Figure: Block diagram of Tacotron 2 system architecture⁹

⁹J. Shen, R. Pang, R. J. Weiss, et al., "Natural TTS Synthesis by Conditioning WaveNet on Mel Spectrogram Predictions," en, *arXiv:1712.05884 [cs]*, Dec. 2017, arXiv: 1712.05884. [Online]. Available: <http://arxiv.org/abs/1712.05884> (visited on 10/08/2019).

Mel spectrogram

- ▶ Related to the short-time Fourier transform (STFT)
- ▶ Obtained by applying a nonlinear transform to the frequency axis of the STFT
- ▶ Emphasizes details in lower frequencies
- ▶ De-emphasizes high frequency details

Features derived from the mel scale have been used as an underlying representation for speech recognition for many decades.¹⁰

¹⁰S. Davis and P. Mermelstein, "Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences," *IEEE transactions on acoustics, speech, and signal processing*, vol. 28, no. 4, pp. 357–366, 1980.

Tacotron 2: Training

Feature detection network

- ▶ Maximum likelihood training procedure
- ▶ Batch size = 64 on a single GPU
- ▶ Adam optimizer w/
 $\beta_1 = 0.9$, $\beta_2 = 0.999$,
 $\epsilon = 10^{-6}$
- ▶ LR = 10^{-3} , exponentially
decaying to 10^{-5}
- ▶ Warmup training till 50,000
iterations
- ▶ L2 regularization with
weight 10^{-6}

WaveNet

- ▶ Batch size = 128 on 32
GPUs
- ▶ Adam optimizer w/
 $\beta_1 = 0.9$, $\beta_2 = 0.999$,
 $\epsilon = 10^{-8}$
- ▶ Fixed LR = 10^{-4}
- ▶ Exponentially-weighted
moving average of the
network parameters over
update steps with a decay of
0.9999
- ▶ Scaling by 127.5
- ▶ US English dataset

Tacotron 2: Evaluation

- ▶ 100 random examples from test set sent to Mechanical Turk
- ▶ Each sample is rated by atleast 8 raters
- ▶ Scores on a scale of 1 to 5 with 0.5 increments

Tacotron 2: Reported results

System	MOS
Parametric	3.492 ± 0.096
Tacotron (Griffin-Lim)	4.001 ± 0.087
Concatenative	4.166 ± 0.091
WaveNet (Linguistic)	4.341 ± 0.051
Ground truth	4.582 ± 0.053
Tacotron 2 (this paper)	4.526 ± 0.066

Figure: Mean Opinion Scores (MOS)¹¹

¹¹J. Shen, R. Pang, R. J. Weiss, *et al.*, "Natural TTS Synthesis by Conditioning WaveNet on Mel Spectrogram Predictions," *en, arXiv:1712.05884 [cs]*, Dec. 2017, arXiv: 1712.05884. [Online]. Available: <http://arxiv.org/abs/1712.05884> (visited on 10/08/2019).

Conclusions and future strategies

- ▶ More general models
- ▶ More languages
- ▶ Names, abbreviations, context require more work
- ▶ Better evaluation and testing required

References I

1. A. v. d. Oord, S. Dieleman, H. Zen, *et al.*, “WaveNet: A Generative Model for Raw Audio,” *en, arXiv:1609.03499 [cs]*, Sep. 2016, arXiv: 1609.03499. [Online]. Available: <http://arxiv.org/abs/1609.03499> (visited on 10/08/2019)
2. J. Shen, R. Pang, R. J. Weiss, *et al.*, “Natural TTS Synthesis by Conditioning WaveNet on Mel Spectrogram Predictions,” *en, arXiv:1712.05884 [cs]*, Dec. 2017, arXiv: 1712.05884. [Online]. Available: <http://arxiv.org/abs/1712.05884> (visited on 10/08/2019)
3. K. KIM, *WaveNet: Increasing reception field using dilated convolution*, <https://medium.com/@kion.kim/wavenet-a-network-good-to-know-7caaae735435>, [Online; accessed 10/09/2019]

References II

4. S. Kumar, *Understanding WaveNet architecture*, <https://medium.com/@satyam.kumar.iiitv/understanding-wavenet-architecture-361cc4c2d623>, [Online; accessed 10/09/2019]
5. J. Singh, *WaveNet: Google Assistant's Voice Synthesizer*, <https://towardsdatascience.com/wavenet-google-assistants-voice-synthesizer-a168e9af13b1>, [Online; accessed 10/09/2019]
6. Q. Yongliang, *Behind WaveNet*, https://ctmakro.github.io/site/on_learning/audio/wavenet_arch.html, [Online; accessed 10/09/2019]
7. D. Mwiti, *A 2019 guide to speech synthesis with deep learning*, <https://heartbeat.fritz.ai/a-2019-guide-to-speech-synthesis-with-deep-learning-630afcafb9dd>, [Online; accessed 10/09/2019]