

# E3 TTS: EASY END-TO-END DIFFUSION-BASED TEXT TO SPEECH

Yuan Gao, Nobuyuki Morioka, Yu Zhang, Nanxin Chen

Google

{gaoyua, nmorioka, ngyuzh, nanxinchen}@google.com

## ABSTRACT

We propose **Easy End-to-End Diffusion-based Text to Speech**, a simple and efficient end-to-end text-to-speech model based on diffusion. E3 TTS directly takes plain text as input and generates an audio waveform through an iterative refinement process. Unlike many prior work, E3 TTS does not rely on any intermediate representations like spectrogram features or alignment information. Instead, E3 TTS models the temporal structure of the waveform through the diffusion process. Without relying on additional conditioning information, E3 TTS could support flexible latent structure within the given audio. This enables E3 TTS to be easily adapted for zero-shot tasks such as editing without any additional training. Experiments show that E3 TTS can generate high-fidelity audio, approaching the performance of a state-of-the-art neural TTS system. Audio samples are available at <https://e3tts.github.io>.

**Index Terms**— text-to-speech, non-autoregressive, diffusion, diversity

## 1. INTRODUCTION

Diffusion models [1, 2, 3] have demonstrated great performance on a variety of generation tasks, including image [4, 5, 6] and audio generation [7, 8]. Diffusion models work by gradually removing noise from a latent representation of the data until it becomes indistinguishable from real data. Text-to-speech (TTS) systems that use diffusion models have been shown to produce high-fidelity speech that is comparable with state-of-the-art systems [7, 8, 9, 10].

Most prior work in this area has relied on a two-stage generation process. In the first stage, the generator model generates intermediate representations, typically audio tokens [11, 12] or spectrogram-based features [13, 14, 15, 16, 17, 18, 19], which are aligned with the waveform but in lower resolution. In the second stage, a vocoder is introduced to predict the audio from the intermediate features. Besides the two-stage process, most models take some extra neural model or statistical method to convert the text to some other input units [20], such as phonemes or graphemes.

Even though a two-stage TTS pipeline can produce higher quality audio, it may also have other concerns, such as rely-

ing on the quality of intermediate features. Additionally, it is more complicated to deploy and set up for different situations.

End-to-end generation of audio from text is elusive, due to the difficulty of efficiently modeling strong temporal dependencies in the waveform. Sample-level autoregressive vocoders handle such dependencies by conditioning generation of each waveform sample on the whole history. Due to their highly sequential nature, they are inefficient to sample from on modern parallel hardware. Some previous work instead generates a sequence of non-overlapping fixed-length blocks autoregressively to speedup the generation [21]. This speeds up the generation process by generating all samples within the block in parallel.

A different direction of prior work is to include alignment information during training. The alignment information provides the mapping between each individual input unit, such as a phoneme, and output samples in the generated audio. It is usually extracted using external alignment tools, which provide the start time and end time of each individual input unit. FastSpeech 2 [22] relies on such alignment or duration information and other properties such as energy and pitch to predict the audio. One internal predictor is also trained for each individual property so the predicted results could be utilized during inference. EATS [23] proposes to use a differentiable duration predictor and depends on the Dynamic Time Wrapping (DTW) to make sure the prediction is aligned with the target audio. This avoids the usage of external aligner but makes the training more complicated.

In this paper, we propose a **Easy End-to-End Text to Speech** framework (E3 TTS) that only relies on diffusion to preserve temporal structure in waveform. It directly takes text as input and uses a pretrained BERT model [24] to extract information from it. It is followed by a UNet structure [25] which predicts the audio by attending to the BERT representations. The whole model is non-autoregressive and directly outputs a waveform. Our model achieves comparable results to the two-stage framework on proprietary dataset from experiments.

The paper is organized as follows. Section 2 gives a brief overview of different components used in prior works of TTS that could be optimized. Section 3 introduces the proposed system which only includes a diffusion model taking BERT representations as input. Section 4 starts with experiments

on proprietary dataset, comparing with some previous work. Section 5 reveals some applications that could be achieved with the proposed method. Section 6 summarizes the system and discusses some future work.

## 2. COMPLEXITIES OF TTS

Through a careful analysis of current text-to-speech (TTS) systems, we have identified several components that greatly increase the complexities of existing systems.

### 2.1. Text Normalization

One of the challenges in building a text-to-speech (TTS) system is the normalization of input text. This is the process of converting text from its written form into a form that can be easily processed by the TTS system. This can be a difficult task, as there are many different ways that text can be written [20]. For example, the same word can be written in different ways, such as "color" and "colour". Additionally, text can contain abbreviations, acronyms, and other non-standard forms. A good TTS system must be able to handle all of these different variations in order to produce accurate and natural-sounding speech.

### 2.2. Input Unit

Even after text normalization, there can still be ambiguities in how to pronounce the same word in different contexts. For example, *record* has different pronunciations depending whether it is a noun or a verb. This is why many TTS systems rely on verbalized forms, such as phonemes or prosodic features, instead of text directly.

**Phonemes:** A phoneme is a unit of sound that is used to make up words. Many previous work [7, 10] rely on phonemes as input. This can be useful for generating speech from languages that do not have a standard writing system.

**Prosodic features:** Prosodic features are characteristics of speech, such as fundamental frequencies, durations, and energy. Some previous work [13, 22] utilize prosodic features as input. This can be used to control the intonation and emphasis of the generated speech.

### 2.3. Alignment Modeling

Another challenge in building a TTS system is alignment modeling. This is the process of predicting the length of time that each phoneme in a word should be pronounced. This is important because it helps to ensure that the generated speech sounds natural and fluent. Alignment modeling can be a difficult task, as there are many factors that can affect the length of time that a phoneme is pronounced. For example, the position of a phoneme in a word can affect its duration. Additionally, the stress of a word can also affect the duration of its phonemes. A good TTS system must be able to

model all of these factors in order to produce accurate and natural-sounding speech.

A typical approach for alignment modeling in end-to-end speech-to-text system is to rely on external aligner which provides the alignment information given transcript and audio [13, 10]. During model training, a duration predictor is learned to predict the information which could be used to estimate alignment for inference. For duration predictor, Non-Attentive Tacotron framework [15] managed to learn duration implicitly by employing the Variational Auto-Encoder. Glow-TTS [26] and Grad-TTS [27] made use of Monotonic Alignment Search algorithm (an adoption of Viterbi training [28] finding the most likely hidden alignment between two sequences). Indeed, we actually solve the quality issue Grad-TTS mentioned in paper when they try to conduct end-to-end experiments.

## 3. METHOD

We propose our solution that addresses challenges presented in the last Section to make TTS systems more accessible to the wider community. The proposed model includes two modules illustrated in Figure 1:

- A pretrained BERT model extracts information from text.
- An diffusion UNet model attends to the BERT output and predicts the raw waveform by refining the noisy waveform iteratively.

### 3.1. BERT model

To take the advantage of the recent large language model development, we built our system based on the text representations which are given by a pretrained BERT model [24]. The BERT model takes the subword as input and it does not rely on any other presentations of the speech such as phoneme, graphemes, in contrast to some previous work [15, 16, 14, 13, 22, 21, 29, 30]. This simplifies the process since one could rely on a pretrained text language model which could be trained on multiple languages with only text data available.

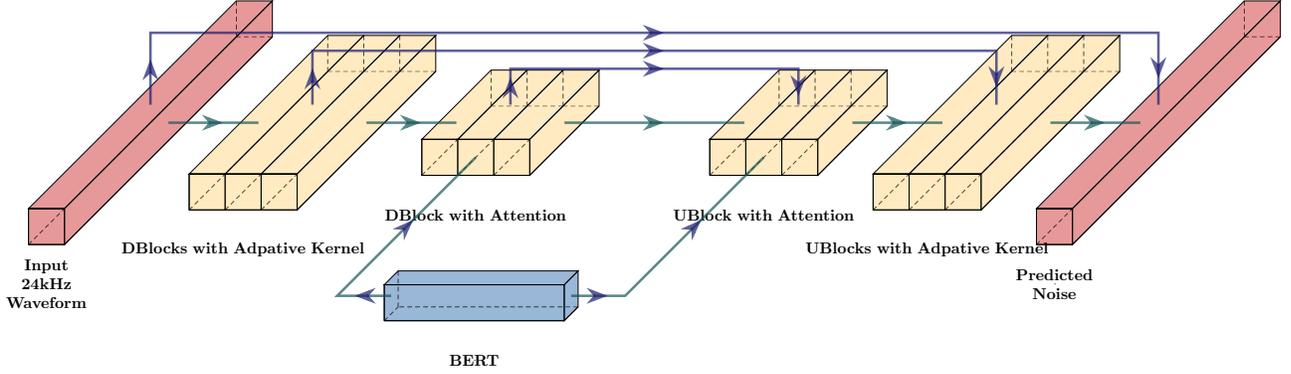
### 3.2. Diffusion

Our model is built based on prior work on score matching [3] and diffusion probabilistic models [1]. In the case of TTS, the score function is defined as the gradient of the log conditional distribution  $p(y | x)$  with respect to the output  $y$  as

$$s(y | x) = \nabla_y \log p(y | x) \quad (1)$$

where  $y$  is the waveform and  $x$  is the conditioning signal.

Following previous work [9], we adopt a special parameterization known as the diffusion model [1]. A score network



**Fig. 1.** UNet Structure: DBlock for downsampling block, UBlock for upsampling block

$s(\tilde{y} | x, \bar{\alpha})$  is trained to predict the scaled derivative by minimizing the distance between model prediction and ground truth  $\epsilon$  as

$$\mathbb{E}_{\bar{\alpha}, \epsilon} \left[ \left\| \epsilon_{\theta}(\tilde{y}, x, \sqrt{\bar{\alpha}}) - \epsilon \right\|_2 \right] \quad (2)$$

where  $\epsilon \sim \mathcal{N}(0, I)$  is the noise term introduced by applying the reparameterization trick,  $\bar{\alpha}$  is the noise level and  $\tilde{y}$  is sampled according to

$$\tilde{y} = \sqrt{\bar{\alpha}} y_0 + \sqrt{1 - \bar{\alpha}} \epsilon \quad (3)$$

During training,  $\bar{\alpha}$ 's are sampled from the intervals  $[\bar{\alpha}_n, \bar{\alpha}_{n+1}]$  based on a pre-defined linear schedule of  $\beta$ 's, according to:

$$\bar{\alpha}_n := \prod_{s=1}^n (1 - \beta_s) \quad (4)$$

In each iteration, the updated waveform is estimated following the following stochastic process

$$y_{n-1} = \frac{1}{\sqrt{\alpha_n}} \left( y_n - \frac{\beta_n}{\sqrt{1 - \bar{\alpha}_n}} \epsilon_{\theta}(y_n, x, \sqrt{\bar{\alpha}_n}) \right) + \sigma_n z \quad (5)$$

In this work, to help convergence and to better scale  $\epsilon$  loss's magnitude, we adopt a KL form loss. The model also predicted the variance  $\omega(\alpha)$  of the L2 loss according to timestep, and we use a KL loss form to adjust the weight of the loss from different sampled timestep.

$$\mathbb{E}_{\bar{\alpha}, \epsilon} \left[ \frac{1}{\omega(\bar{\alpha})} \left\| \epsilon_{\theta}(\tilde{y}, x, \sqrt{\bar{\alpha}}) - \epsilon \right\|_2 + \ln(\omega(\bar{\alpha})) \right] \quad (6)$$

### 3.3. U-Net

We deploy a 1D U-Net, following the structure of [4]. The general model structure are shown in Figure 1, consists of a series of downsampling and upsampling blocks connected by residual. The detailed structure of each downsampling/upsampling block is shown in Figure 2. Like the typical

approach in autoregressive TTS [31, 32], we adopt a **cross-attention** to extract information from BERT output in the top downsampling/upsampling blocks. In the low downsampling/upsampling block, following [33], we use an adaptive softmax CNN kernel whose kernel is determined by timestep and speaker. In other layers, speaker and timestep embedding are joined using FiLM [34], which comprises a combined layer which predicts channel-wise scaling and bias. Inside each block, ublock and dblock the structure closely follow the structure described in [4].

The downsampler finally refined the noise information (24kHz) to a sequence whose length is similar to the encoded BERT output. This has proved important in practice to improve the quality. The upsampler finally predicts noise whose length is the same as the input waveform.

In training, we fixed the length of waveform to be 10.92 sec, and padding zero to the end of the waveform. When calculating loss, the padding part are less weighted. In practice, we weight each padding frame  $\frac{1}{10}$  as non-padding frame. In inference, we fixed the length of output waveform. And we use average magnitude to distinguish the padding part. In practice, we calculate average magnitude per 1024 samples and cutoff  $\leq 0.02$  parts.

## 4. EXPERIMENT

We compare our model with other neural TTS systems. Following [9], baseline systems were trained on a proprietary dataset consisted of 385 hours of high-quality US English speech from 84 professional voice talents. A female speaker was chosen from the training dataset for evaluation. We implemented our model with parameter size in Table 1. For pre-trained BERT, we take base parameter size model trained on English only data<sup>1</sup>. In inference, we use 1000 steps DDPM,

<sup>1</sup>English only, uncased BERT-Base model provided in <https://github.com/google-research/bert>

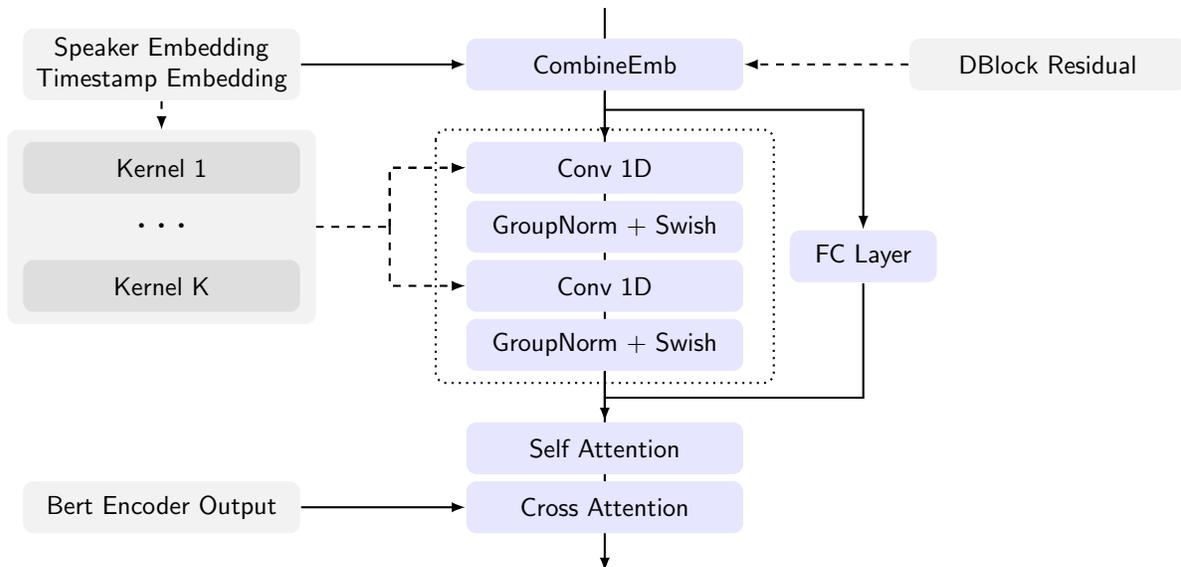


Fig. 2. UBlock/DBlock Structure: Adaptive Kernel and residual optional.

noise scheduling is

$$\alpha_n = \exp(\ln(1e-7) * (1 - \cos(\frac{n}{1000} * \frac{\pi}{2})))^{\frac{3}{2}} \quad (7)$$

Performance is measured using subjective listening tests, performed by a pool of native speakers listening with headphones. Results are reported as the mean opinion score (MOS) which measures the naturalness of generated sample on a ten-point scale from 1 to 5. Each sample is rated at least twice by two different native speakers. We compared our model with character based TTS models from [21], the result are shown in Table 2.

Block index	0	1	2	3
Base dimension	128	256	512	1024
Kernel Size	[5,5]	[5,5]	[5,5]	[3,3,3,3,3]
Strides	[2,2]	[2,2]	[4]	[4,2,2,2,2]
Adaptive Kernel	[8,8]	[4,4]	[2]	
Blocks	[2,2]	[2,2]	[2]	[1,1,1,1,1]
Self Attention	[×,×]	[×,×]	[×]	[√,√,√,√,√]
Cross Attention	[×,×]	[×,×]	[×]	[√,√,√,√,√]
Attention Heads				[8,8,8,8,8]

Table 1. Model configuration. Empty cell indicates it is not used in this block.

Results suggest the proposed method leads to a better fidelity than other end-to-end systems. One minor difference here is that the proposed system is based on sub-word instead of characters but we believe it should be comparable for TTS application.

Mode	MOS
<b>Ground truth</b>	4.56 ± 0.04
<b>Two-Stage Models</b>	
Tacotron-PN + Griffin-Lim [35] (char)	3.68 ± 0.08
Tacotron + WaveRNN [36] (char)	<b>4.36 ± 0.05</b>
Tacotron + Flowcoder [37] (char)	3.34 ± 0.07
<b>End-to-End Models</b>	
Wave-Tacotron [21] (char)	4.07 ± 0.06
Our Model	<b>4.24 ± 0.06</b>

Table 2. TTS performance on the proprietary single speaker dataset, evaluation contains about 600 examples.

## 5. APPLICATIONS

In this Section, we demonstrate our model could be applied in different scenarios. Specifically, we use a base model trained without any speaker information provided. The speaker is dynamically determined during inference. To enlarge the speaker diversity, we train the model on all LibriTTS data, mixing clean-100, clean-360, other-500 splits.

### 5.1. Zero Shot Learning

In the proposed approach, the alignment between the audio and text features is dynamically determined during inference. This enables zero-shot learning for a variety of applications. We demonstrate the model’s ability through the following tasks. Examples of each task and corresponding audio samples are displayed on <https://e3tts.github.io>.

### 5.1.1. Waveform Prompt based TTS

For this task, for each example, we select two sentences from same speaker from test split of LibriTTS-clean. We concatenate the text of sentences and provide the waveform of first sentence as the prompt to the model. The prompt part are guaranteed to be longer than 3 seconds, and the part asked to be generated are guaranteed to be longer than 2 seconds, the total length are guaranteed to be shorter than 9 seconds. During inference, on the prompt part, we replace the predicted  $\epsilon$  with actual  $\epsilon$ . And on the rest, we keep the predicted  $\epsilon$ . Quantitative results are shown in the top part of Table 3. We report SQuId score [38] which is an approximation of the mean opinion score, and speaker similarity (Speaker Sim). Speaker similarity is estimated based on the speaker embedding given by a LSTM-based speaker model [39]. Results demonstrate that our model could generate high-quality audio given prompt with similar speaker characteristics.

### 5.1.2. Text-based Speech Editing

To evaluate the model’s ability to edit speech, we evaluate the performance of text-based speech inpainting, which is a special case of replacement. We select sentences from test split of LibriTTS-clean and masked a small fragment (0.5 secs  $\sim$  2.5 secs) in waveform. We then provide the sentences, the masked waveform to the model, and ask it to get the whole waveform. Similar to the audio prompt task, we replace the predicted  $\epsilon$  with true  $\epsilon$  on the unchanged audio and keep the rest. In practice, the length of the masked part is unknown, and is usually provided by the user or predicted by some other model in a statistical way. To show the ability of diffusion model, we feed 3 example of same sentence to the model, with different masked part length(0.8 $\times$ , 1.0 $\times$ , 1.2 $\times$  the ground truth length), and reported their result in Table 3. From the experiment results, we can conclude that the proposed model E3 is robust against different lengths of editing span.

Task	Split	SQuId	Speaker Sim
Prompt TTS	Ground Truth	3.81	
	Our Model	<b>3.75</b>	<b>0.95</b>
Text Editing	Ground Truth	3.91	
	0.8 $\times$	<b>3.84</b>	0.98
	1.0 $\times$	3.83	<b>0.98</b>
	1.2 $\times$	3.81	0.97
	Best of 3	3.85	0.98

**Table 3.** Audio prompt and text-based editing results. Metrics include SQuId which approximates mean opinion score and speaker similarity. Prompt TTS task contains about 200 examples. Text Editing task contains about 80 examples. Evaluation data are generated from test split of LibriTTS

### 5.1.3. Speaker Similarity

For this task, we select sentence from random unseen speakers from test split of LibriTTS-clean. For each example, we select waveform  $w_A$  from Speaker A and 8 waveform  $w_B^1 \dots w_B^8$  from random selected speakers (Speaker A must be included). We ask model to predict which speaker  $w_A$  belongs to. In inference, we concatenate the  $w_A$  and  $w_B^i$  and get 8 waveform. We random select a timestep ( $0.04 \leq \alpha_n \leq 0.96$ ) and feed the noised waveform to the model. Similar to [40], we calculated the L2 distance on predicted  $\epsilon$  and true  $\epsilon$  and sum them up using a fixed calculated weight. To make the result independent to  $w_B^i$ ’s magnitude and length, we only take the  $\epsilon$  part on  $w_A$  in consideration. We summarize the result from different timestep samples using Monte Carlo method. The result for different sample times are listed in 4. In general, with more timestep sampled, we observe better speaker accuracy. The result itself is interesting especially since the model is trained without any speaker information.

#Timesteps	Speaker Classification Accuracy
1 sample	75.50%
4 samples	81.00%
32 samples	<b>83.20%</b>

**Table 4.** Speaker similarity results evaluated on about 1000 examples. With more sampled steps, we observe better classification accuracy.

## 5.2. Sample Diversity

	Fréchet Speaker Distance
Ground Truth	8.38
Wave-Tacotron	26.58
Our Model	<b>12.30</b>

**Table 5.** Fréchet Speaker Distance results on proprietary dataset. Fréchet Speaker Distance measures the audio diversity. FSD of the ground truth is measured by computing the score between non-overlap subsets of ground truth audio.

Diffusion models can generate samples with higher diversity and with more authentic distribution. To measure distribution, inspired by FID [41] and FAD [42], we introduce new metric called Fréchet Speaker Distance (FSD). We use a LSTM-based speaker model [39] and take the normalized last embedding layer. And calculate the distance using

$$FSD_{A,B} = \|\mu_A - \mu_B\|^2 + Tr(C_A + C_B - 2\sqrt{C_A * C_B}) \tag{8}$$

where  $\mu$  represent the mean of model output speaker embedding among all examples,  $C$  represent the covariance.

We evaluate our model’s FSD score on proprietary dataset. Results in Table 5 reveals the proposed E3 TTS system greatly improves the diversity comparing to previous work. It reaches similar score as the ground truth.

## 6. CONCLUSION

We have proposed a novel end-to-end text-to-speech (TTS) model, E3, that is capable of generating high-fidelity audio directly from BERT features. E3 is based on the diffusion model, an iterative refinement process. The alignment between the audio and text features is dynamically determined during generation using cross attention. E3 greatly simplifies the design of end-to-end TTS systems and has been shown to achieve impressive performance in experiments. We also demonstrate that this simplified architecture enables a variety of zero-shot tasks, such as speech editing and prompt-based generation.

In future work, we plan to extend E3 to support multilingual speech generation by replacing the English-only BERT model with a multilingual language model.

## 7. REFERENCES

- [1] Jonathan Ho, Ajay Jain, and Pieter Abbeel, “Denoising diffusion probabilistic models,” *Advances in neural information processing systems*, vol. 33, pp. 6840–6851, 2020.
- [2] Jascha Sohl-Dickstein, Eric Weiss, Niru Maheswaranathan, and Surya Ganguli, “Deep unsupervised learning using nonequilibrium thermodynamics,” in *International conference on machine learning*. PMLR, 2015, pp. 2256–2265.
- [3] Yang Song, Jascha Sohl-Dickstein, Diederik P Kingma, Abhishek Kumar, Stefano Ermon, and Ben Poole, “Score-based generative modeling through stochastic differential equations,” *arXiv preprint arXiv:2011.13456*, 2020.
- [4] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily Denton, Seyed Kamyar Seyed Ghasemipour, Raphael Gontijo-Lopes, Burcu Karagol Ayan, Tim Salimans, Jonathan Ho, David J. Fleet, and Mohammad Norouzi, “Photorealistic text-to-image diffusion models with deep language understanding,” in *Advances in Neural Information Processing Systems*, Alice H. Oh, Alekh Agarwal, Danielle Belgrave, and Kyunghyun Cho, Eds., 2022.
- [5] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen, “Hierarchical text-conditional image generation with clip latents,” *arXiv preprint arXiv:2204.06125*, 2022.
- [6] Emiel Hoogeboom, Jonathan Heek, and Tim Salimans, “simple diffusion: End-to-end diffusion for high resolution images,” *arXiv preprint arXiv:2301.11093*, 2023.
- [7] Nanxin Chen, Yu Zhang, Heiga Zen, Ron J Weiss, Mohammad Norouzi, and William Chan, “Wavegrad: Estimating gradients for waveform generation,” in *International Conference on Learning Representations*, 2021.
- [8] Zhifeng Kong, Wei Ping, Jiaji Huang, Kexin Zhao, and Bryan Catanzaro, “Diffwave: A versatile diffusion model for audio synthesis,” in *International Conference on Learning Representations*, 2020.
- [9] Nanxin Chen, Yu Zhang, Heiga Zen, Ron J. Weiss, Mohammad Norouzi, Najim Dehak, and William Chan, “Wavegrad 2: Iterative refinement for text-to-speech synthesis,” in *Proc. Interspeech*. 2021, pp. 3765–3769, ISCA.
- [10] Zhijun Liu, Yiwei Guo, and Kai Yu, “Diffvoice: Text-to-speech with latent diffusion,” in *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2023, pp. 1–5.
- [11] Chengyi Wang, Sanyuan Chen, Yu Wu, Ziqiang Zhang, Long Zhou, Shujie Liu, Zhuo Chen, Yanqing Liu, Huaming Wang, Jinyu Li, et al., “Neural codec language models are zero-shot text to speech synthesizers,” *arXiv preprint arXiv:2301.02111*, 2023.
- [12] Zalán Borsos, Raphaël Marinier, Damien Vincent, Eugene Kharitonov, Olivier Pietquin, Matt Sharifi, Dominik Roblek, Olivier Teboul, David Grangier, Marco Tagliasacchi, et al., “Audiolm: a language modeling approach to audio generation,” *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 2023.
- [13] Yi Ren, Yangjun Ruan, Xu Tan, Tao Qin, Sheng Zhao, Zhou Zhao, and Tie-Yan Liu, “Fastspeech: Fast, robust and controllable text to speech,” *Advances in neural information processing systems*, vol. 32, 2019.
- [14] Naihan Li, Shujie Liu, Yanqing Liu, Sheng Zhao, and Ming Liu, “Neural speech synthesis with transformer network,” in *Proceedings of the AAAI conference on artificial intelligence*, 2019, vol. 33, pp. 6706–6713.
- [15] Jonathan Shen, Ye Jia, Mike Chrzanowski, Yu Zhang, Isaac Elias, Heiga Zen, and Yonghui Wu, “Non-attentive tacotron: Robust and controllable neural tts synthesis including unsupervised duration modeling,” *arXiv preprint arXiv:2010.04301*, 2020.

- [16] Isaac Elias, Heiga Zen, Jonathan Shen, Yu Zhang, Ye Jia, Ron J Weiss, and Yonghui Wu, "Parallel tacotron: Non-autoregressive and controllable tts," in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2021, pp. 5709–5713.
- [17] Heeseung Kim, Sungwon Kim, and Sungroh Yoon, "Guided-tts: A diffusion model for text-to-speech via classifier guidance," 2022.
- [18] Jaesung Tae, Hyeongju Kim, and Taesu Kim, "Editts: Score-based editing for controllable text-to-speech," 2022.
- [19] Zhifang Guo, Yichong Leng, Yihan Wu, Sheng Zhao, and Xu Tan, "Prompttts: Controllable text-to-speech with text descriptions," in *ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2023, pp. 1–5.
- [20] Richard Sproat, "Boring problems are sometimes the most interesting," *Computational Linguistics*, vol. 48, no. 2, pp. 483–490, 2022.
- [21] Ron J Weiss, RJ Skerry-Ryan, Eric Battenberg, Soroosh Mariooryad, and Diederik P Kingma, "Wave-tacotron: Spectrogram-free end-to-end text-to-speech synthesis," in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2021, pp. 5679–5683.
- [22] Yi Ren, Chenxu Hu, Xu Tan, Tao Qin, Sheng Zhao, Zhou Zhao, and Tie-Yan Liu, "Fastspeech 2: Fast and high-quality end-to-end text to speech," in *International Conference on Learning Representations*, 2021.
- [23] Jeff Donahue, Sander Dieleman, Mikolaj Binkowski, Erich Elsen, and Karen Simonyan, "End-to-end adversarial text-to-speech," in *International Conference on Learning Representations*, 2021.
- [24] Jacob Devlin Ming-Wei Chang Kenton and Lee Kristina Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of NAACL-HLT*, 2019, pp. 4171–4186.
- [25] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Medical Image Computing and Computer-Assisted Intervention—MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18*. Springer, 2015, pp. 234–241.
- [26] Jaehyeon Kim, Sungwon Kim, Jungil Kong, and Sungroh Yoon, "Glow-tts: A generative flow for text-to-speech via monotonic alignment search," in *Proceedings of the 34th International Conference on Neural Information Processing Systems*, Red Hook, NY, USA, 2020, NIPS'20, Curran Associates Inc.
- [27] Vadim Popov, Ivan Vovk, Vladimir Gogoryan, Tasnima Sadekova, and Mikhail Kudinov, "Grad-tts: A diffusion probabilistic model for text-to-speech," in *Proceedings of the 38th International Conference on Machine Learning*, Marina Meila and Tong Zhang, Eds. 18–24 Jul 2021, vol. 139 of *Proceedings of Machine Learning Research*, pp. 8599–8608, PMLR.
- [28] L.R. Rabiner, "A tutorial on hidden markov models and selected applications in speech recognition," *Proceedings of the IEEE*, vol. 77, no. 2, pp. 257–286, 1989.
- [29] Yuxuan Wang, Daisy Stanton, Yu Zhang, RJ-Skerry Ryan, Eric Battenberg, Joel Shor, Ying Xiao, Ye Jia, Fei Ren, and Rif A Saurous, "Style tokens: Unsupervised style modeling, control and transfer in end-to-end speech synthesis," in *International conference on machine learning*. PMLR, 2018, pp. 5180–5189.
- [30] RJ Skerry-Ryan, Eric Battenberg, Ying Xiao, Yuxuan Wang, Daisy Stanton, Joel Shor, Ron Weiss, Rob Clark, and Rif A Saurous, "Towards end-to-end prosody transfer for expressive speech synthesis with tacotron," in *international conference on machine learning*. PMLR, 2018, pp. 4693–4702.
- [31] Wenfu Wang, Shuang Xu, and Bo Xu, "First Step Towards End-to-End Parametric TTS Synthesis: Generating Spectral Parameters with Neural Attention," in *Proc. Interspeech 2016*, 2016, pp. 2243–2247.
- [32] Yuxuan Wang, R.J. Skerry-Ryan, Daisy Stanton, Yonghui Wu, Ron Weiss, Navdeep Jaitly, Zongheng Yang, Ying Xiao, Zhifeng Chen, Samy Bengio, Quoc Le, Yannis Agiomyrgiannakis, Rob Clark, and Rif Saurous, "Tacotron: Towards end-to-end speech synthesis," 08 2017, pp. 4006–4010.
- [33] Minguk Kang, Jun-Yan Zhu, Richard Zhang, Jaesik Park, Eli Shechtman, Sylvain Paris, and Taesung Park, "Scaling up GANs for Text-to-Image Synthesis," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 10124–10134.
- [34] Ethan Perez, Florian Strub, Harm de Vries, Vincent Dumoulin, and Aaron Courville, "Film: Visual reasoning with a general conditioning layer," 2017.
- [35] D. Griffin and Jae Lim, "Signal estimation from modified short-time fourier transform," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 32, no. 2, pp. 236–243, 1984.

- [36] Nal Kalchbrenner, Erich Elsen, Karen Simonyan, Seb Noury, Norman Casagrande, Edward Lockhart, Florian Stimberg, Aaron van den Oord, Sander Dieleman, and Koray Kavukcuoglu, “Efficient neural audio synthesis,” in *Proceedings of the 35th International Conference on Machine Learning*, Jennifer Dy and Andreas Krause, Eds. 10–15 Jul 2018, vol. 80 of *Proceedings of Machine Learning Research*, pp. 2410–2419, PMLR.
- [37] Sungwon Kim, Sang-Gil Lee, Jongyoon Song, Jaehyeon Kim, and Sungroh Yoon, “FloWaveNet : A generative flow for raw audio,” in *Proceedings of the 36th International Conference on Machine Learning*, Kamalika Chaudhuri and Ruslan Salakhutdinov, Eds. 09–15 Jun 2019, vol. 97 of *Proceedings of Machine Learning Research*, pp. 3370–3378, PMLR.
- [38] Thibault Sellam, Ankur Bapna, Joshua Camp, Diana Mackinnon, Ankur P Parikh, and Jason Riesa, “Squid: Measuring speech naturalness in many languages,” in *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2023, pp. 1–5.
- [39] Rajeev Rikhye, Quan Wang, Qiao Liang, Yanzhang He, Ding Zhao, Arun Narayanan, Ian McGraw, et al., “Personalized keyphrase detection using speaker and environment information,” in *Proc. Interspeech*. 2021, pp. 4204–4208, ISCA.
- [40] Alexander C Li, Mihir Prabhudesai, Shivam Duggal, Ellis Brown, and Deepak Pathak, “Your diffusion model is secretly a zero-shot classifier,” *arXiv preprint arXiv:2303.16203*, 2023.
- [41] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter, “GANs Trained by a Two Time-Scale Update Rule Converge to a Local Nash Equilibrium,” *Advances in neural information processing systems*, vol. 30, 2017.
- [42] Kevin Kilgour, Mauricio Zuluaga, Dominik Roblek, and Matthew Sharifi, “Fréchet audio distance: A metric for evaluating music enhancement algorithms,” in *Proc. Interspeech*. 2019, pp. 2350–2354, ISCA.