DEEP VOICE 3: 2000-SPEAKER NEURAL TEXT-TO-SPEECH

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ABSTRACT

We present Deep Voice 3, a fully-convolutional attention-based neural text-to-speech (TTS) system. Deep Voice 3 matches state-of-the-art neural speech synthesis systems in naturalness while training ten times faster. We scale Deep Voice 3 to data set sizes unprecedented for TTS, training on more than eight hundred hours of audio from over two thousand speakers. In addition, we identify common error modes of attention-based speech synthesis networks, demonstrate how to mitigate them, and compare several different waveform synthesis methods. We also describe how to scale inference to ten million queries per day on one single-GPU server.

1 INTRODUCTION

Artificial speech synthesis, also called text-to-speech (TTS), is traditionally done with complex multi-stage hand-engineered pipelines (Taylor, 2009). Recent work on neural TTS has demonstrated impressive results – yielding pipelines with simpler features, fewer components, and higher quality synthesized speech. There is not yet a consensus on the optimal neural network architecture for TTS, however, sequence-to-sequence models (Wang et al., 2017; Sotelo et al., 2017; Arık et al., 2017) have shown to be quite promising.

In this paper, we propose a novel fully-convolutional architecture for speech synthesis, scale it to very large audio data sets, and address several real-world issues that come up when attempting to deploy an attention-based TTS system. Specifically, we make the following contributions:

1. We propose a fully-convolutional character-to-spectrogram architecture, which enables fully paralleled computation over elements in a sequence and trains an order of magnitude faster than analogous architectures using recurrent cells (e.g., Wang et al., 2017).

2. We show that our architecture trains quickly and scales to the LibriSpeech dataset (Panayotov et al., 2015), which consists of nearly 820 hours of audio data from 2484 speakers.

3. We demonstrate that we can generate monotonic attention behavior, avoiding error modes commonly occurred in speech synthesis.

4. We compare the quality of several waveform synthesis methods for a single speaker, including WORLD (Morise et al., 2016), Griffin-Lim (Griffin & Lim, 1984), and WaveNet (Oord et al., 2016).

5. We describe the implementation of an inference kernel for Deep Voice 3, which can serve up to ten million queries per day on one single-GPU server.

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2 RELATED WORK

Our work builds upon the state-of-the-art in neural speech synthesis and attention-based sequence-to-sequence learning.

Several recent works tackle the problem of synthesizing speech with neural networks, including Deep Voice 1 (Arık et al., 2017), Deep Voice 2 (Arık et al., 2017), Tacotron (Wang et al., 2017), Char2Wav (Sotelo et al., 2017), VoiceLoop (Taigman et al., 2017), SampleRNN (Mehri et al., 2017), and WaveNet (Oord et al., 2016). Deep Voice 1 & 2 retain the traditional structure of TTS pipelines, separating grapheme-to-phoneme conversion, duration and frequency prediction, and waveform synthesis. In contrast to Deep Voice 1 & 2, Deep Voice 3 employs an attention-based sequence-to-sequence model, yielding a more compact architecture. Similar to Deep Voice 3, Tacotron and Char2Wav are the two proposed sequence-to-sequence models for neural TTS. Tacotron is a neural text-to-spectrogram conversion model, used with Griffin-Lim for spectrogram-to-waveform synthesis. Char2Wav predicts the parameters of WORLD vocoder (Morise et al., 2016) and uses a SampleRNN conditioned upon WORLD parameters for waveform generation. In contrast to Char2Wav and Tacotron, Deep Voice 3 avoids Recurrent Neural Networks (RNNs)\(^1\) to speed up training and alleviates several challenging error modes that attention models fall into. Thus, Deep Voice 3 makes attention-based TTS feasible for a production TTS system with no compromise on accuracy. Finally, WaveNet and SampleRNN are proposed as neural vocoder models for waveform synthesis. It is also worth noting that there are numerous alternatives for high-quality hand-engineered vocoders in the literature, such as STRAIGHT (Kawahara et al., 1999), Vocaine (Agiomyrgiannakis, 2015), and WORLD (Morise et al., 2016). Deep Voice 3 adds no novel vocoder, but has the potential to be integrated with different waveform synthesis methods with slight modifications of its architecture.

The automatic speech recognition (ASR) dataset can be very large in scale, but are typically recorded under various conditions and with varying microphones, that are not as perfectly clean as ideal TTS corpora. Our work is not the first to attempt a multi-speaker TTS system on ASR corpora. For example, Yamagishi et al. (2010) builds several speaker-adaptive HMM-based TTS systems (Yamagishi et al., 2009) on various ASR corpora with hundreds of speakers. Nonetheless, to the best of our knowledge, Deep Voice 3 is the first TTS system to scale to thousands of speakers.

Sequence-to-sequence models (Sutskever et al., 2014; Cho et al., 2014) encode a variable-length input to hidden states, and which are then processed at the decoder to generate the target sequence. An attention mechanism allows the decoder to adaptively choose which hidden states in encoder to focus on while generating the target sequence (Bahdanau et al., 2015). Attention-based sequence-to-sequence models are widely applied in machine translation (Bahdanau et al., 2015), speech recognition (Chorowski et al., 2015), and text summarization (Rush et al., 2015). Recent improvements in attention mechanisms relevant to Deep Voice 3 include enforced-monotonic attention during training (Raffel et al., 2017), fully-attentional non-recurrent architectures (Vaswani et al., 2017), and convolutional sequence-to-sequence models (Gehring et al., 2017). Deep Voice 3 demonstrates the utility of monotonic attention during training in TTS, a new domain where monotonicity is expected. Alternatively, we show that with a simple heuristic to only enforce monotonicity during inference, a standard attention mechanism can work just as well or even better. Deep Voice 3 also builds upon the convolutional sequence-to-sequence architecture from Gehring et al. (2017) by introducing a positional encoding similar to that used in Vaswani et al. (2017), augmented with a rate adjustment to account for the mismatch between input and output domain lengths.

3 MODEL ARCHITECTURE

In this section, we present our fully-convolutional sequence-to-sequence architecture for TTS (see Fig. 1). Our architecture is capable of converting a variety of textual features (characters, phonemes, stresses) to a variety of acoustic features (mel-band spectrograms, linear-scale log magnitude spectrograms, or a set of vocoder features such as fundamental frequency, spectral envelope, and aperiodicity parameters). These acoustic features can then be inputs for audio waveform synthesis models. Deep Voice 3 architecture consists of three components:

- **Encoder**: A fully-convolutional encoder, which converts textual features to an internal learned representation.

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\(^{1}\)RNNs process each state sequentially and thus make model parallelism very challenging to utilize fully.
Figure 1: Deep Voice 3 uses residual convolutional layers to encode textual features into per-timestep key and value vectors for an attention-based decoder. The decoder uses these to predict the mel-band log magnitude spectrograms that correspond to the output audio. (Light blue dotted arrows depict the autoregressive synthesis process during inference.) The hidden states of the decoder are then fed to a converter network to predict the acoustic features for waveform synthesis. Please see Appendix A for more details.

- **Decoder**: A fully-convolutional causal decoder, which decodes the learned representation with a multi-hop convolutional attention mechanism into a low-dimensional audio representation (mel-band spectrograms) in an auto-regressive manner.

- **Converter**: A fully-convolutional post-processing network, which predicts final output features (depending on the waveform synthesis method) from the decoder hidden states. Unlike the decoder, the converter is non-causal and can thus depend on future context information.

The overall objective function to be optimized is a linear combination of the losses from the decoder (Section 3.4) and the converter (Section 3.6). The whole model is trained in an end-to-end manner, excluding the vocoder (WORLD, Griffin-Lim, or WaveNet). In multi-speaker scenario, trainable speaker embeddings as in Arik et al. (2017) are used across encoder, decoder and converter. Next, we describe each of these components and the data preprocessing in detail. Model hyperparameters are available in Table 4 within Appendix C.

3.1 **Text Preprocessing**

Text preprocessing is crucial for good performance. Feeding raw text (characters with spacing and punctuation) yields acceptable performance on many utterances. However, some utterances will have mispronunciations of rare words, or have skipped words and repeated words. We alleviate these issues by normalizing the input text as follows:

1. We uppercase all characters in the input text.
2. We remove all intermediate punctuation marks.
3. We end every utterance with a period or question mark.
4. We replace spaces between words with special separator characters which indicate the duration of pauses inserted by the speaker between words.

3.2 **Joint Representation of Characters and Phonemes**

Deployed TTS systems (e.g., Capes et al., 2017; Gonzalvo et al., 2016) should include a way to modify pronunciations to correct common mistakes (which typically include proper nouns, foreign words, and domain-specific jargon). A conventional way to do this is maintaining a dictionary mapping words to their phonetic representations and manually editing it in the case of errors.

2We use four different word separators, indicating slurred-together words, standard pronunciation and space characters, a short pause between words, and a long pause between words. The pause durations can be obtained through either manual labeling or by estimated by a text-audio aligner such as Gentle (Oehshorn & Hawkins, 2017). For example, the sentence “Either way, you should shoot very slowly,” with a long pause after “way” and a short pause after “shoot”, would be written as “Either way%you should shoot/very slowly%.” with % representing a long pause and / representing a short pause for encoding convenience. Our single-speaker dataset is labeled by hand and our multi-speaker datasets are annotated using Gentle.
Our model can directly convert characters (including punctuation and spacing) to acoustic features, and hence learns an implicit grapheme-to-phoneme model. An implicit conversion is difficult to correct when the model makes mistakes. Thus, in addition to character models, we also train phoneme-only models and mixed character-and-phoneme models by allowing phoneme input option explicitly. These models are identical to character-only models, except for the input layer of the encoder, which takes phoneme and phoneme stress embeddings instead of or in addition to character embeddings.

A phoneme-only model requires a preprocessing step to convert words to their phoneme representations (by using an external phoneme dictionary or a separately trained grapheme-to-phoneme model)\(^1\). A mixed character-and-phoneme model requires a similar preprocessing step, except for words not in the phoneme dictionary. These out-of-vocabulary words are input as characters, allowing the model to use its implicitly learned grapheme-to-phoneme model. While training a mixed character-and-phoneme model, every word is replaced with its phoneme representation with some fixed probability (e.g., 0.9) at each training iteration. We find that augmenting phonemes as input improves performance in terms of pronunciation accuracy and minimizing attention errors, especially when generalizing to utterances longer than those in the training set. More importantly, models that support phonemes representation allow correcting mispronunciations by editing the phoneme dictionary, which is a highly preferred feature in real-world production system.

### 3.3 Encoder

The encoder network (depicted in Fig. 1) begins with an embedding layer, which converts characters or phonemes into trainable vector representations. These embeddings \(h_e\) are projected via a fully-connected layer from the embedding dimension to a target dimensionality, followed by a series of convolution blocks (Fig. 2a), and then projected back to the embedding dimension to create the attention key vectors \(h_k\). The attention value vectors are given by \(h_v = \sqrt{0.5}(h_k + h_e)\). The key vectors \(h_k\) are used by each attention block to compute attention weights, whereas the final context vector is computed as a weighted average over the value vectors \(h_v\) (see Section 3.5).

\[ h_v = \sqrt{0.5}(h_k + h_e) \]

**Figure 2:** (a) The convolution block consists of a 1-D convolution with gated linear unit (Dauphin et al., 2017) and residual connection. (b) Four fully-connected layers generate WORLD features.

The convolution blocks (depicted in Fig. 2a) used in our encoder and elsewhere in the architecture consist of a convolution, a gated-linear unit as the nonlinear activation, a residual connection to the input, and a scaling factor of \(\sqrt{0.5}\). To preserve the sequence length, inputs are padded with \(k-1\) timesteps of zeros on the left (for causal convolutions) or \((k-1)/2\) timesteps of zeros on the left and on the right (for standard non-causal convolutions), where \(k\) is an odd convolution filter width \(^3\). Dropout is applied to the inputs prior to the convolution.

\(^1\)In this work, we use CMUDict 0.6b.

\(^3\)The scaling factor ensures that we preserve the input variance early in training. We initialize the convolution filter weights as in Gehring et al. (2017) to start training with zero-mean and unit-variance activations throughout the entire network.

\(^3\)We restrict to odd convolution widths to simplify the convolution arithmetic.
3.4 Decoder

The decoder (depicted in Fig. 1) generates audio in an autoregressive manner by predicting a group of future audio frames given all past audio frames. Since the decoder is autoregressive, it must use exclusively causal convolutions. Audio frames are processed in groups of \( r \) frames and are represented by a low-dimensional mel-band log-magnitude spectrogram. The choice of \( r \) can have a significant impact on the performance, as decoding several frames together is better than simply decoding one, which confirms a similar result from Wang et al. (2017).

The decoder network consists of several fully-connected layers with rectified linear unit (ReLU) nonlinearities, a series of attention blocks (described in Section 3.5), and finally fully-connected output layers which predict the next group of \( r \) audio frames and also a binary “done” prediction (indicating whether the last frame of the utterance has been synthesized). Dropout is applied before each fully-connected layer prior to the attention blocks, except for the very first one. An L1 loss is computed using the output spectrograms and a binary cross-entropy loss is computed using the “done” prediction.

3.5 Attention Block

![Attention Block Diagram](image)

Figure 3: Positional encodings are added to both keys and query vectors, with rates of \( \omega_{\text{key}} \) and \( \omega_{\text{query}} \) respectively. Forced monotonocity can be applied at inference by adding a mask of large negative values to the logits. One of two possible attention schemes is used: softmax or monotonic attention from Raffel et al. (2017). During training, attention weights are dropped out.

We use a dot-product attention mechanism (depicted in Fig. 3) similar to Vaswani et al. (2017). The attention mechanism uses a query vector (the hidden state of the decoder) and the per-timestep key vectors from the encoder to compute attention weights, and then outputs a context vector computed from the weighted average of the value vectors.

In addition to the embeddings generated by the encoder and decoder, we add a positional encoding to both the key and the query vectors. These positional encodings \( h_p \) are computed as \( h_p(i) = \sin(\omega_i/10000^{k/d}) \) (for even \( i \)) or \( \cos(\omega_i/10000^{k/d}) \) (for odd \( i \)), where \( i \) is the timestep index, \( k \) is the channel index in the positional encoding, \( d \) is the total number of channels in the positional encoding, and \( \omega \) is the position rate of the encoding. The position rate dictates the average slope of the line in the attention distribution, roughly corresponding to speed of speech. For a single speaker, \( \omega \) is set to one for the decoder and fixed for the encoder to the ratio of output timesteps to input timesteps (computed across the entire dataset). For multi-speaker datasets, \( \omega \) is computed for both the encoder and decoder from the speaker embedding for each speaker (depicted in Fig. 3). As sine and cosine functions form an orthonormal basis, this initialization creates a favorable inductive bias for the model as the attention distribution due to positional encodings is effectively a straight diagonal line (Fig. 4).
Figure 4: Attention distributions (a) before training, (b) after training, but without inference constraints, (c) with inference constraints applied to the first and third layers. (We empirically observe that fixing the attention of one or two dominant layers is sufficient for high-quality output.)

Weinitialize the fully-connected layer weights used to compute hidden attention vectors to the same values for the query projection and the key projection. Positional encodings are used in all attention blocks. We use context normalization as in (Gehring et al., 2017). A fully-connected layer is applied to the context vector to generate the output of the attention block.

When using this attention mechanism, positional encodings greatly improve quality and are key to having a functional convolutional attention mechanism. However, even with the positional encodings, the model may sometimes repeat or skip words. We consider two different mechanisms to alleviate this. The first mechanism is imposing constraint during inference that attention is monotonic: instead of computing the softmax over the entire input, we instead compute the softmax only over a fixed window starting at the last attended-to position and going forward several timesteps.\(^6\)

The attended-to position is initially set to zero and later computed as the index of the highest attention weight within the current window. Visualization of the attention distributions of this approach is shown in Fig. 4. The second mechanism is applying the monotonic attention introduced in Raffel et al. (2017), which, unlike the generic attention with inference constraint, incorporates the monotonicity during training. In practice, both approaches work well for creating a clear, monotonic attention curve, but using monotonic attention during training results in the model frequently mumbling words.

3.6 Converter

The converter network takes as inputs the activations from the last hidden layer of the decoder, applies several non-causal convolution blocks, and then predicts parameters for downstream waveform generation models. Unlike the decoder, the converter is non-causal and non-autoregressive, so it can use future context from the decoder to predict its outputs.

The loss function of converter network depends on the type of downstream vocoders:

1. L1 loss on linear-scale (log-magnitude) spectrograms for use with Griffin-Lim,
2. L1 and cross entropy losses on parameters of WORLD vocoder (see Fig. 2b),
3. L1 loss on linear-scale (log-magnitude) spectrograms for use with WaveNet neural vocoder.

For Griffin-Lim audio synthesis, we also find that using a pre-emphasis along with raising the spectrogram to a power before waveform synthesis is helpful for improved audio quality, as suggested in Wang et al. (2017). For the WORLD vocoder, we predict a boolean value (whether the current frame is voiced or unvoiced), an F0 value (if the frame is voiced), the spectral envelope, and the aperiodicity parameters. We use a cross-entropy loss for the voiced-unvoiced prediction and L1 losses for all other predictions. For WaveNet vocoder, we use mel-scale spectrograms from the decoder in inference, and feed them as the conditioner for WaveNet, which is separately trained.\(^7\)

\(^6\)We use the window size as 3 in all the experiments.

\(^7\)Note that this differs from Arık et al. (2017) as it used linear-scale log-magnitude spectrograms. We typically observe better performance with a lower dimensional conditioner for WaveNet.
Text Input & Attention & Inference constraint & Repeat & Mispronounce & Skip 

Characters-only & Dot-Product & Yes & 3 & 35 & 19 

Phonemes & Characters & Dot-Product & No & 12 & 10 & 15 

Phonemes & Characters & Dot-Product & Yes & 1 & 4 & 3 

Phonemes & Characters & Monotonic & No & 5 & 9 & 11 

Table 1: Counted attention errors of single-speaker Deep Voice 3 models on the 100-sentence test set, which is given in Appendix E. Phonemes& Characters refers to the model trained by using joint representation of characters and phonemes as discussed in Section 3.2. As there are out-of-vocabulary words, we didn’t include phoneme-only model. All models assume Griffin-Lim as the vocoder. Any mispronunciation, skipping or repeating errors in each sentence is counted as one - in other words, every entry in the table is upper limited by 100.

4 RESULTS

In this section, we present several different experiments and metrics that have been useful for the development of a production-quality speech synthesis system. We quantify the performance of our system and compare it to other recently published neural TTS systems.

Data: For single-speaker synthesis, we use an internal English speech data set containing approximately 20 hours data with the sampling rate of 48 KHz. For multi-speaker synthesis, we use VCTK and LibriSpeech data sets. VCTK dataset consists audios for 108 speakers, with a total duration of ~44 hours. LibriSpeech data set consists audios for 2484 speakers, with a total duration of ~820 hours. The sampling rate for VCTK is 48 KHz, whereas for LibriSpeech is 16 KHz.

Fast Training: We compare Deep Voice 3 to Tacotron, a recently published attention-based TTS system. For our system on single-speaker data, the average training iteration time (for batch size 4) is 0.06 seconds using one GPU as opposed to 0.59 seconds for Tacotron, indicating a ten-fold increase in training speed. In addition, Deep Voice 3 converges after ~500K iterations for all three datasets in our experiment, while Tacotron requires ~2M iterations as suggested in Wang et al. (2017). This significant speedup is due to the fully-convolutional architecture of Deep Voice 3, which highly exploits the parallelism of a GPU during training.

Attention Error Modes: Attention-based neural TTS systems hit several error modes which can reduce synthesis quality – including mispronunciations, skipped words, and repeated words. One reason is that the attention-based architecture does not impose a monotonically progressing distribution. In order to track the occurrence of these errors, we construct a custom 100-sentence test set (see Appendix E) that includes particularly-challenging cases from deployed TTS systems (e.g. dates, acronyms, URLs, repeated words, proper nouns, foreign words etc.) Counted attention errors are listed in Table 1 and indicate that the model with joint representation of characters and phonemes, trained with standard attention mechanism but enforced the monotonic constraint at inference, largely outperforms other approaches.

Naturalness: We demonstrate that choice of waveform synthesis matters for naturalness ratings and compare it to other published neural TTS systems. Results in Table 2 indicate that WaveNet, a neural vocoder, achieves the highest MOS of 3.78, followed by WORLD and Griffin-Lim at 3.63 and 3.62, respectively. Thus, we show that the most natural waveform synthesis can be done with a neural vocoder and that basic spectrogram inversion techniques can match advanced vocoders. The WaveNet vocoder sounds more natural as the WORLD vocoder introduces various noticeable artifacts. Yet, lower inference latency may render WORLD vocoder preferable: the heavily engineered WaveNet implementation runs at 3X realtime per CPU core (Arık et al., 2017), while in our testing WORLD runs up to 40X realtime per CPU core (see the subsection below).

Multi-Speaker Synthesis: To demonstrate that our model is capable of handling multi-speaker speech synthesis effectively, we train our models on the VCTK and LibriSpeech data sets. For LibriSpeech (as it is an ASR data set), we apply a preprocessing step of standard denoising (using SoX (Bagwell, 2017)) and splitting long utterances into multiple at pause locations (which are determined by Gentle (Ochshorn & Hawkins, 2017)) to improve performance. We use Griffin-Lim and WORLD as the vocoder for VCTK, and only Griffin-Lim for LibriSpeech due to its efficiency. Results are presented in Table 3. We purposefully include ground-truth samples in the set being evalu-
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| Model | Mean Opinion Score (MOS) |
|-------|--------------------------|
| Deep Voice 3 (Griffin-Lim) | 3.62 ± 0.31 |
| Deep Voice 3 (WORLD) | 3.63 ± 0.27 |
| Deep Voice 3 (WaveNet) | 3.78 ± 0.30 |
| Tacotron (Griffin-Lim) | 1.77 ± 0.19 |
| Tacotron (WaveNet) | 3.78 ± 0.34 |
| Deep Voice 2 (WaveNet) | 2.74 ± 0.35 |

Table 2: Mean Opinion Score (MOS) ratings with 95% confidence intervals using different waveform synthesis methods. We use the crowdMOS toolkit (Ribeiro et al., 2011); batches of samples from these models were presented to raters on Mechanical Turk. Since batches contained samples from all models, the experiment naturally induces a comparison between the models.

| Model | MOS (VCTK) | MOS (LibriSpeech) |
|-------|------------|-------------------|
| Deep Voice 3 (Griffin-Lim) | 3.01 ± 0.29 | 2.09 ± 0.31 |
| Deep Voice 3 (WORLD) | 3.44 ± 0.32 | - |
| Deep Voice 2 (WaveNet) | 3.69 ± 0.23 | - |
| Tacotron (Griffin-Lim) | 2.07 ± 0.31 | - |
| Ground truth | 4.69 ± 0.04 | 4.60 ± 0.16 |

Table 3: MOS ratings with 95% confidence intervals for audio clips from neural TTS systems on multi-speaker datasets. To obtain MOS, we also use crowdMOS toolkit as detailed in Table 2.

ated, because the accents in datasets are likely to be unfamiliar to our North American crowdsourced raters and will thus be rated poorly due to the accent rather than the model quality. Our model with WORLD vocoder archives a comparable MOS of 3.44 on VCTK in contrast to 3.66 from Deep Voice 2, which is the state-of-the-art multi-speaker neural TTS using WaveNet as vocoder and separately optimized duration and frequency prediction building blocks. We expect further improvement by using WaveNet for multi-speaker synthesis, although it will substantially slow down the system at inference. The MOS on LibriSpeech is lower, which we mainly attribute to the lower quality of the training dataset due to various recording conditions. Lastly, we observe that the learned speaker embeddings lie in a meaningful latent space (see Fig. 6 in Appendix D).

Optimizing Inference for Deployment: In order to deploy a neural TTS system in a cost-effective manner, the system must be able to handle as much traffic as alternative systems on a comparable amount of hardware. To do so, we target a throughput of ten million queries per day or 116 queries per second (QPS) on a single-GPU server with twenty CPU cores, which we find is comparable in cost to commercially deployed TTS systems. By implementing custom GPU kernels for the Deep Voice 3 architecture and parallelizing WORLD synthesis across CPUs, we demonstrate that our model can handle ten million queries per day. One can find more details in Appendix B.

5 Conclusion

We introduce Deep Voice 3, a neural text-to-speech system based on a novel fully-convolutional sequence-to-sequence acoustic model with a position-augmented attention mechanism. We describe common error modes in sequence-to-sequence speech synthesis models and show that we successfully avoid these common error modes with Deep Voice 3. We show that our model is agnostic of the waveform synthesis method, and adapt it for Griffin-Lim spectrogram inversion, WaveNet, and WORLD vocoder synthesis. We demonstrate also that our architecture is capable of multispeaker speech synthesis by augmenting it with trainable speaker embeddings, a technique described in Deep Voice 2. Finally, we describe the production-ready Deep Voice 3 system in full including text normalization and performance characteristics, and demonstrate state-of-the-art quality through extensive MOS evaluations. Future work will involve improving the implicitly learned grapheme-to-phoneme model, jointly training with a neural vocoder, and training on cleaner and larger datasets to scale to model the full variability of human voices and accents from hundreds of thousands of speakers.

A query is defined as synthesizing the audio for a one second utterance.
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Appendices

A Detailed Model Architecture of Deep Voice 3

The detailed model architecture is depicted in Fig. 5.

Figure 5: Deep Voice 3 uses a deep residual convolutional network to encode text and/or phonemes into per-timestep key and value vectors for an attentional decoder. The decoder uses these to predict the mel-band log magnitude spectrograms that correspond to the output audio. (Light blue dotted arrows depict the autoregressive synthesis process during inference.) The hidden state of the decoder then gets fed to a converter network to output linear spectrograms for Griffin-Lim or parameters for WORLD, which can be used to synthesize the final waveform. Weight normalization (Salimans & Kingma, 2016) is applied to all convolution filters and fully-connected layer weight matrices in the model.

B Optimizing Deep Voice 3 for Deployment

Running inference with a TensorFlow graph turns out to be prohibitively expensive, averaging approximately 1 QPS \(^9\). Instead, we implement custom GPU kernels for Deep Voice 3 inference. Due to the complexity of the model and the large number of output timesteps, launching individual kernels for different operations in the graph (convolutions, matrix multiplications, unary and binary operations etc.) is impractical: the overhead of launch a CUDA kernel is approximately 50 µs, which, when aggregated across all operations in the model and all output timesteps, limits throughput to approximately 10 QPS. Thus, we implement a single kernel for the entire model, which avoids the overhead of launching many CUDA kernels. Finally, instead of batching computation in the kernel, our kernel operates on a single utterance and we launch as many concurrent streams as there are Streaming Multiprocessors (SMs) on the GPU. Every kernel is launched with one block, so we expect the GPU to schedule one block per SM, allowing us to scale inference speed linearly with the number of SMs.

On a single P100 GPU with 56 SMs, we achieve an inference speed of 115 QPS, which corresponds to our target ten million queries per day. We parallelize WORLD synthesis across all 20 CPUs on

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\(^9\)The poor TensorFlow performance is due to the overhead of running the graph evaluator over hundreds of nodes and hundreds of timesteps. Using a technology such as XLA with TensorFlow could speed up evaluation but is unlikely to match the performance of a hand-written kernel.
the server, permanently pinning threads to CPUs in order to maximize cache performance. In this setup, GPU inference is the bottleneck, as WORLD synthesis on 20 cores is faster than 115 QPS.

We believe that inference can be made significantly faster through more optimized kernels, smaller models, and fixed-precision arithmetic; we leave these aspects to future work.

C Model Hyperparameters

All hyperparameters of the models used in this paper are shown in Table 4.

| Parameter                              | Single-Speaker | VCTK          | LibriSpeech   |
|----------------------------------------|----------------|---------------|---------------|
| FFT Size                               | 4096           | 4096          | 4096          |
| FFT Window Size / Shift                | 2400 / 600     | 2400 / 600    | 16000 / 400   |
| Audio Sample Rate                      | 48000          | 48000         | 16000         |
| Reduction Factor r                     | 4              | 4             | 4             |
| Mel Bands                              | 80             | 80            | 80            |
| Sharpening Factor                      | 1.4            | 1.4           | 1.4           |
| Character Embedding Dim.               | 256            | 256           | 256           |
| Encoder Layers / Conv. Width / Channels| 7 / 5 / 64     | 7 / 5 / 128   | 7 / 5 / 256   |
| Decoder Affine Size                    | 128, 256       | 128, 256      | 128, 256      |
| Decoder Layers / Conv. Width           | 4 / 5          | 6 / 5         | 8 / 5         |
| Attention Hidden Size                  | 128            | 256           | 256           |
| Position Weight / Initial Rate         | 1.0 / 6.3      | 0.1 / 7.6     | 0.1 / 2.6     |
| Converter Layers / Conv. Width / Channels| 5 / 5 / 256   | 6 / 5 / 256   | 8 / 5 / 256   |
| Dropout Probability                    | 0.95           | 0.95          | 0.99          |
| Number of Speakers                     | 1              | 108           | 2484          |
| Speaker Embedding Dim.                 | -              | 16            | 32            |
| ADAM Learning Rate                     | 0.001          | 0.0005        | 0.0005        |
| Anneal Rate / Anneal Interval          | -              | 0.98 / 30000  | 0.95 / 30000  |
| Batch Size                             | 16             | 16            | 16            |
| Max Gradient Norm                      | 100            | 100           | 50.0          |
| Gradient Clipping Max. Value           | 5              | 5             | 5             |

Table 4: Hyperparameters used for best models for the three datasets used in the paper.

D Latent Space of the Learned Embeddings

Similar to Arik et al. (2017), we apply principal component analysis to the learned speaker embeddings and analyze the speakers based on their ground truth genders. Fig. 6 shows the genders of the speakers in the space spanned by the first two principal components. We observe a very clear separation between male and female genders, suggesting the low-dimensional speaker embeddings constitute a meaningful latent space.
Figure 6: The first two principal components of the learned embeddings for (a) VCTK dataset (108 speakers) and (b) LibriSpeech dataset (2484 speakers).

E 100-SENTENCE TEST SET

The 100 sentences used to quantify the results in Table 1 are listed below (note that % symbol corresponds to pause):
Under review as a conference paper at ICLR 2018

1. A B C
2. X Y Z
3. HUGTY
4. WOBBLE
5. REFERENDUM
6. IS IT FREE?
7. JUSTIFIABLE
8. ENVIRONMENT
9. A DRUM RUMBLE
10. GRAVITATIONAL
11. CARDBOARD FILM
12. PERSON THINKING
13. PREPARED MURDERERS
14. AIRCRAFT TORTURES
15. ALLERGIC TROUSERS
16. STRATEGIC CONDUCT
17. WORRYING LITERATURE
18. CHRISTMAS IS COMING
19. A DOSS DILEMMA THINKS
20. HOW WAS THE MATH TEST?
21. GOOD TO THE LAST DROP
22. AN M B A AGENT LISTENS
23. A COMPLICATED DISAPPEARANCE
24. AN AXIS OF X Y OR Z FREEZES
25. SHE DID HER BEST TO HELP HIM
26. A BACKBONE CONTESTS THE CHAMPIONSHIP
27. TWO A GREATER THAN TWO EXIDE
28. DON'T STEP ON THE BROKEN GLASS
29. A DAMNED FLIPS INTO THE PATIENTS
30. A TRADE PURGES WITHIN THE B B C
31. I'D RATHER BE A BIRD THAN A FISH
32. I HEAR THAT NANCY IS VERY PRETTY
33. I WANT MORE DETAILED INFORMATION
34. PLEASE WAIT OUTSIDE THE HOUSE
35. N A S A EXPOSURE TUNES THE WAFLE
36. A MIST DICTATES WITHIN THE MONSTER
37. A PREPARES THE MIDDLE CEREMONY
38. EVERY FAREWELL EXPLODES THE CAKE
39. SHE FOLDED HER HANDKERCHIEF NEATLY
40. AGAINST THE STEAM CHISELS THE STUDIO
41. ROCK MUSIC APPROACH AT HIGH VELOCITY
42. NING ANG HAYE STUDY ON THE TWO PIECES
43. AN UNFRIENDLY DECAY CONVEYS THE OUTCOME
44. ABSTRACTION IS OFTEN ONE FLOOR ABOVE YOUR
45. A PLAYED LADY RANKS ANY PUBLICIZED PREVIEW
46. HE TOLD US A VERY EXCITING ADVENTURE STORY
47. ON AUGUST TWENTY EIGHTH STAYPLAYS THE PIANO
48. INTO A CONTROLLER BEANS A CONCRETE TERRORIST
49. I OFTEN SEE THE TIME ELEVEN ELEVEN ON CLOCKS
50. IT WAS GETTING DARK AND WE WEREN'T THERE YET
51. AGAINST EVERY EMERGE STAPLES A CHORAL APPARATUS
52. EVERYONE WAS BUSY SO I WENT TO THE MOVIE ALONE
53. I CHECKED TO MAKE SURE THAT HE WAS STILL ALIVE
54. A DOMINANT VEGETARIAN SHIDS AWAY FROM THE G O P
55. OCE MADE THE SUGAR COOKIES DECORATED THEM
56. I WANT TO BUY A ONE-EIGHTH UNKNOOW IT DON'T SUIT ME
57. A FAMOUS OVERRIDE OF Q W E R T Y OUTSIDE THE POPE
58. T B I SAYS THAT C I A SAYS I'LL STAY AWAY FROM IT
59. ANY CLIMBING DISH LISTENS TO A CUMBERSOME FORMULA
60. SHE WROTE HIM A LONG LETTER BUT HE DIDN'T READ IT
61. A RBABY IS IN THE HEAD NOT PHYSICAL A RIVE YOU
62. AN APPEAL ON JANUARY FIFTH DUPLICATES A SHARP QUEEN
63. A FAREWELL SONGS ON MARCH TWENTY THIRD SHAKES NORTH
64. HE RAN OUT OF MONEY SO HE HAD TO STOP PLAYING POKER
65. FOR EXAMPLE A NEWSPAPER HAS ONLY REGIONAL DISTRIBUTION T-days.
66. I CURRENTLY HAVE FOUR WINDOWS OPEN AND I DON’T KNOW WHY.
67. NEXT TO MY INDIRECT VOCAL DECLINES EVERY UNBEARABLE ACADEMIC.
68. OPPOSITE HER SECONDING DAD IS A M C’S CONFIGURED THOROUGHLY.
69. FROM APRIL EIGHTH TO THE PRESENT I ONLY SMOKED FOUR CIGARETTES.
70. I WILL NEVER BE THIS YOUNG AGAIN! EVER! OH DAMN! JUST OLDERS.
71. A GENTLE CONTINUUM OF AMAZON DOT COM IS THE CONFLICTING WORKERS.
72. SHE ADVISED HIM TO COME BACK AT ONCE THE WIFE LECTURES THE BLAST.
73. A SONG CAN MAKE OR RUIN A PERSON’S DAY IF THEY LET IT GET TO THEM.
74. SHE DID NOT CREAT ON THE TEST FOR IT WAS NOT THE RIGHT THING TO DO.
75. HE SAID HE WAS NOT THERE YESTERDAY BUT NEVER M ANYONE SAW HIM THERE.
76. SHOULD WE START CLASS NOW OR SHOULD WE WAIT FOR EVERYONE TO GET HERE?
77. IF PURPLE PEOPLE EATERS ARE REAL WHERE DO THEY FIND PURPLE PEOPLE TO EAT?
78. ON NOVEMBER EIGHTEENTH EIGHTEEN TWENTY ON A CLUTTERING GEN IS NOT ENOUGH.
79. A ROCKET FROM SPACE X INTERACTS WITH THE INDIVIDUAL BENEATH THE SOFT BLANK.
80. MALLS ARE GREAT PLACES TO SHOP IF I CAN FIND EVERYTHING I NEED UNDER ONE ROOF.
81. I THINK I WILL BUY THE RED CARPET I WILL LEAVE THE BLUE ONE THE FAITH WAPP.
82. ITALY IS MY FAVORITE COUNTRY IN FACT I PLAN TO SPEND TWO WEEKS THERE NEXT YEAR.
83. I WOULD HAVE GOTTEN W W W DOT GOOGLE DOT COM BUT MY ATTENDANCE WASN’T GOOD ENOUGH.
84. NINETEEN TWENTY IS WHEN WE ARE UNIQUE TOGETHER UNTIL WE REALISE WE ARE ALL THE DAMN.
85. MY MUM TRIES TO BE COOL BY SAYING R T T P COLON SLASH SLASH W W B A I D U DOT COM.
86. HE TURNED IN THE RESEARCH PAPER ON FRIDAY OTHERWISE SHE EMAILED A J D F AT YAHOO DOT OCH.
87. SHE WORKS TWO JOBS TO MAKE ENDS MEET AT LEAST THAT WAS HER REASON FOR NOT HAVING TIME TO JOIN US.
88. A REMARKABLE WELL PROMOTES THE ALPHABET INTO THE ADJUSTED LUCK THE DRESS DODGES ACROSS MY ASSAULT.
89. A R C D R F H J K L M N O P Q R S T U V W X Y Z ONE TWO THREE FOUR FIVE SIX SEVEN EIGHT NINE TEN.
90. Across the waste persists the wrong pacifier the washed passenger parades under the incorrect computer.
91. IF THE EASTER BUNNY AND THE TOOTH FAIRY HAD BABIES WOULD THEY TAKE YOUR TEETH AND LEAVE CHOCOLATE FOR Y O U ?
92. SOMETIMES ALL YOU NEED TO DO IS COMPLETELY MAKE AN ASS OF YOURSELF AND LAUGH IT OFF TO REALISE THAT LIFE ISN’T SO BAD AFTER ALL.
93. SHE BORROWED THE BOOK FROM HIM MANY YEARS AGO AND HASN’T YET RETURNED IT WHY WON’T THE DISTINGUISHING LOVE JUMP WITH THE JUKEBOXER?
94. LAST FRIDAY IN THREE WEEK’S TIME I SAW A SPOTTED STRIPED BLUE WORM SHAKE H A N D S WITH A LEGLESS LIZARD THE LAKE IS A LONG WAY FROM HERE.
95. I WAS VERY PROUD OF MY NICKNAME THROUGHOUT HIGH SCHOOL BUT TODAY I COULDN’T BE ANY DIFFERENT TO WHAT MY NICKNAME WAS THE METAL IUSTS THE RANGING CAPTAIN CHARTERS THE LINK.
96. I AM HAPPY TO TAKE YOUR DONATION ANY AMOUNT WILL BE GREATLY APPRECIATED THE WAVES WERE CRASHING ON THE SHORES WAS A LOVELY SIGHT THE PARADOX STICKS THIS BOWL ON TOP OF A SPONTANEOUS TEA.
97. A PURPLE PIG AND A GREEN DONKEY FLEW A KITE IN THE MIDDLE OF THE NIGHT AND ENDED UP SUNBURSTING CONTAINED BOMB PUDDLES AS A LOGICAL TARGET THE DIVORCE ATTACKS NEAR A MISSING DOOM THE OPERA FORCES THE DAILY EXAMINER INTO A MURDERER.
98. AS THE MOST FAMOUS SINGER SONGWRITER JAY CHOU GAVE A PERFECT PERFORMANCE IN BEIJING ON MAY TWENTY FOURTH TWENTY FIFTH AND TWENTY SIXTH TWENTY THREE ALL THE FANS THOUGH RICHLY OF HIM AND TOOK PRIDE IN HIM ALL THE TICKETS WERE SOLD OUT.
99. IF YOU LIKE TUNA AND TOMATO SALABILITY COMBINING THE TWO IT’S REALLY NOT AS BAD AS IT SOUNDS THE BODY MAY PERHAPS COMPENSATES FOR THE LOSS OF A TRUE METAPHYSIC THE CLOCK WITHIN THIS BLOG AND THE CLOCK ON MY LAPTOP ARE ONE HOUR DIFFERENT FROM EACH OTHER.
100. SOMEONE I KNOW ADDEDLY COMBINED MAPLE SYRUP AND BUTTERED POPCORN THINKING IT WOULD TASTE LIKE CARAMEL POPCORN IT DIDN’T AND THEY DON’T RECOMMEND ANYONE ELSE DO IT EITHER THE GENTLEMAN MARCHES AROUND THE PRINCIPAL THE DIVORCE ATTACKS NEAR A MISSING DOOM THE COLOR MISPRINTS A CIRCULAR WORRY ACROSS THE CONTROVERSY.