GENERATING GENDER-AMBIGUOUS TEXT-TO-SPEECH VOICES

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ABSTRACT
The gender of a voice assistant or any voice user interface is a central element of its perceived identity. While a female voice is a common choice, there is an increasing interest in alternative approaches where the gender is ambiguous rather than clearly identifying as female or male. This work addresses the task of generating gender-ambiguous text-to-speech (TTS) voices that do not correspond to any existing person. This is accomplished by sampling from a latent speaker embedding space that was formed while training a multilingual, multi-speaker TTS system on data from multiple male and female speakers. Various options are investigated regarding the sampling process. In our experiments, the effects of different sampling choices on the gender ambiguity and the naturalness of the resulting voices are evaluated. The proposed method is shown able to efficiently generate novel speakers that are superior to a baseline averaged speaker embedding. To our knowledge, this is the first systematic approach that can reliably generate a range of gender-ambiguous voices to meet diverse user requirements.

Index Terms— gender-ambiguous, voice generation, text-to-speech, speech synthesis

1. INTRODUCTION
Modern text-to-speech (TTS) synthesis systems are capable of producing high quality synthetic speech, which typically mimics the voice color and style of the speaker in the training data for single-speaker models, or one of the available speakers for models trained on a multi-speaker dataset. The speaker identity representations learned by the TTS model in both cases correspond to a real person, for commercial voices, traditionally a professional voice talent. The development of a new quality voice requires new high-quality recordings, a time-consuming and costly process. Given the rising number of new speaker TTS system on data from multiple male and female speakers. Various options are investigated regarding the sampling process. In our experiments, the effects of different sampling choices on the gender ambiguity and the naturalness of the resulting voices are evaluated. The proposed method is shown able to efficiently generate novel speakers that are superior to a baseline averaged speaker embedding. To our knowledge, this is the first systematic approach that can reliably generate a range of gender-ambiguous voices to meet diverse user requirements.

1.1. Related work
The speaker generation task has been introduced very recently by Stanton et al. [3]. In their work, they train a multi-speaker Tacotron model by using learnable speaker embeddings and create a speaker embedding prior to model the distribution over the speaker embedding space. With this method they are able to create new, natural and non-existent voices. A similar approach has been presented in [4], where the speaker generation task is achieved through a flow-based TTS model [5]. The mel-spectrogram is mapped to a latent representation conditioned on a speaker embedding, then the latent representation is converted back to mel, leveraging the flow’s invertible nature and using a generated speaker embedding as condition. The new speaker embedding is generated by sampling a Gaussian mixture model for each speaker embedding dimension.

Relevant to gender-ambiguous voice generation, in specific, a recent lab report describes preliminary efforts of gender-free style transfer [6]. A gender style recognition model is trained to distinguish between male and female speaking style and then used as a gender style encoder to extract gender embeddings from each utterance. These gender embeddings are used to train a Tacotron TTS model. It is demonstrated that the embeddings are separated according to gender and an attempt is made to calculate a gender-free embedding for use as input to the TTS model during inference.

Gender information is also considered when developing models that preserve the identity of a speaker. In this context, [2] propose gender-ambiguous voice conversion using a GAN-based network and a MelGAN vocoder for privacy preservation purposes.

1.2. Proposed method
We propose a method for generating new, gender-ambiguous, quality voices from binary gendered data. We first train a multi-speaker Tacotron model with a speaker-encoder on multilingual data of various qualities and explore how gender information is encoded in the trained speaker embedding space by examining its correlation to the principal components of that space. We find that much of the gender information tends to be concentrated on few significant components, in our case the first two. We then model separately the density of male and female speakers on those two dimensions and, through these, we estimate an approximate density for gender-ambiguous speakers on that 2D space. For speaker generation, we sample along

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the maxima of this estimated 2D density to obtain the first two dimensions of the generated speaker embedding and then fill-in the rest of the dimensions by interpolating between the closest male and female ground-truth speakers. Several choices are discussed regarding the selection of the closest male and female speakers to interpolate from, such as filtering them based on their quality and/or their language, and using more than two from each gender. We experiment with some of these options by conducting subjective listening tests in English and Korean. This involves generating multiple speakers based on the proposed approach and evaluating them in terms of their naturalness and their gender-ambiguity. The experiments demonstrate that the proposed method is able to efficiently sample the speaker embedding space and generate novel speakers that are superior to a baseline speaker generated by a simple averaging of the embeddings of all ground-truth speakers.

Our contribution lies in the formulation of a method for modeling the gender information in the speaker embedding space and effectively sampling from it to generate novel speakers, as well as in investigating the effect of different sampling options on the perceived gender and naturalness of resulting TTS voices. To the best of our knowledge this is the first systematic approach that can reliably generate a range of alternative gender-ambiguous TTS voices to meet diverse user requirements.

2. EXPERIMENTAL SETUP

2.1. Data

We train our model in a multilingual multi-speaker setup on proprietary and open data. The open datasets utilized are LibriTTS [8] and VCTK [9]. In total, the dataset consists of 866 hours of speech: 1182 (603 males and 579 females) Korean and English speakers where male and female speakers are balanced within each language. All the audio data is sampled to 24kHz. The acoustic features used for training are matching the ones by the LPCNet vocoder [10], i.e. 20 Bark-scale cepstral coefficients (increased by 2 bands compared to LPCNet because of the higher sampling rate), the pitch period and pitch correlation. The input text is normalized and converted into a phoneme sequence by a traditional TTS front-end module.

2.2. Acoustic model architecture

The acoustic model maps the input sequence into a sequence of acoustic feature frames that correspond to the representation used by the LPCNet vocoder [10]. The TTS architecture is based on a Tacotron modification [11] with a duration predictor and a Gaussian upsampler to replace the attention mechanism [12]. In detail, the encoder converts input sequences \( p = [p_1, ..., p_N] \) to learnable embedding vectors, which are then processed by a 2-layer prenet and a CBHG stack from [13] in order to produce the final encoder representation \( e = [e^1, ..., e^N] \). In addition, an embedding layer is introduced, which is essentially a lookup table that stores embeddings of a fixed dictionary and size. In this case, since the speakers involved in the training setup are 1182 and the dimension of each embedding is 64, the produced embedding table has shape of \([1182, 64]\). Then, the speaker embeddings are concatenated with the encoder outputs, before they are fed to the duration prediction, which consists of an LSTM and a linear layer. When decoding is complete, a residual is constructed from a 5-layer convolutional postnet from [15] and added to the output in order to increase the quality of the final outputs. We pair Tacotron with the LPCNet [10] vocoder as adapted for reduced complexity by the parallel work of [16].

3. EMBEDDING GENERATION

3.1. Exploring the speaker embeddings space

As the model is trained on data from various male and female speakers, the speaker encoder’s role is primarily to capture any speaker-specific characteristics of speech. Unavoidably, it also captures all sources of acoustic variation, including differences in environmental noise levels, recording equipment configuration, audio post-processing etc. These variations may be significantly deviant for some subsets of the data and are entangled in the 64-dimensional speaker embedding space formulated by the model during training.

As is often shown in the literature [3], gender is one of the dominant sources of variation in speech. The strength of each dimension’s association with gender in the embedded space can be found using their correlation ratio, \( \eta \), calculated by dividing the weighted variance of the mean of each category (male/female) by the variance of all samples. Fig. 1 shows the correlation ratio of each dimension of the speaker embedding space to gender. While gender information spreads across the dimensions of the plain speaker embeddings (Fig. 1(a)), PCA factors it into much fewer dimensions, notably the first most significant ones (Fig. 1(b)). This clearly demonstrates the role of gender as the main source of variability in the dataset. Fig. 2 provides a 2D projection of the trained speaker embedding space on the first two principal components. As expected, the gender information appears very prominent, and male/female speakers are almost linearly separable. However, additional information, other than gender, is still encoded in these two dimensions. For instance, the VCTK subset accounts for the disperse speakers at the upper-right corner.
method, we need to obtain appropriate values for the rest of the PCA dimensions. The proposed method has ensured that the sampled point lies in an area which is relatively highly populated with ground-truth speakers, both male and female. Thus, a practical approach would be to pick the closest male and female speakers and then just interpolate between them to obtain plausible values for the rest of the dimensions for the sampled 2D vector. This interpolation would be based on a weighted average:

\[ E_a = \frac{\left( \frac{1}{d_m} \cdot E_m + \frac{1}{d_f} \cdot E_f \right)}{\left( \frac{1}{d_m} + \frac{1}{d_f} \right)} \]

where \( E_a \) is the derived speaker embedding for the gender-ambiguous speaker, \( E_m \) and \( E_f \) are the embeddings of the closest male and female speakers, and \( d_m \) and \( d_f \) are the distances of the first two dimensions of \( E_m \) and \( E_f \) from the sampled 2D point.

When it comes to selecting the closest ground-truth speakers to interpolate from, we consider various choices:

\( a. \) Controlling quality of ground-truth speakers. While the multi-speaker speech synthesizer has been trained on ground-truth speaker data from multiple sources of different quality standards and has learned to properly encode them in the speaker embedding space, it may often be desirable to have more control over the quality of the generated synthetic speakers, aiming for cleaner and noise-free voices. In that case, we can use the embedded space learned from the full set of speakers but only choose higher quality male and female speakers during interpolation. This is the approach we follow in Section 4. In specific, we ignore the VCTK speakers when looking for closest male/female ground-truth voices during interpolation, since they seem to significantly deviate from the rest of the voices in terms of the dataset’s overall acoustic conditions. The interpolation between the embeddings of VCTK and non-VCTK speakers for populating the rest of dimensions, would not only encode speaker characteristics but also diverse acoustic conditions, potentially leading to quality degradation and audible artifacts.

\( b. \) Restricting to same-language speakers. It is also possible to impose constraints on the language of the speakers selected for interpolation, i.e. use only English male/female voices to generate gender-ambiguous US English voices. The idea is that this would lead to interpolating between speakers that are, in a sense, more compatible, leading to less degradation in quality. We have experimented with both options, i.e. (i) choosing from both English and Korean ground-truth speakers when interpolating either English and Korean gender-ambiguous voices, and (ii) choosing only among English users when generating gender-ambiguous English speakers.

\( c. \) Interpolating between multiple male and female ground-truth speakers. In some cases it may be beneficial to interpolate between multiple nearby male and female ground-truth speakers in order to smooth out local effects or to compensate for any local irregularities of the speaker embedding space. This was not deemed necessary during our experiments.

Once the sampled speaker embeddings of full dimensions have been obtained in the PCA space, it is straightforward to return to the normal embedding space by applying the inverse PCA transform.

4. EXPERIMENTS AND RESULTS

To assess the proposed method, a number of speaker embeddings have been generated by sampling the 2D PCA space at the points labeled 1 to 10 in Fig. 5. The closest male and female speakers have then been identified from the available pool of ground-truth speakers and then used to interpolate the rest of the dimensions. Following the
method discussed in Section 3.2 two alternative strategies have been examined selecting the ground-truth male and female speakers: (a) among all speakers from both languages excluding only the VCTK speakers: this resulted in the generated speaker embeddings 1-10; and (b) among English speakers only, excluding the VCTK and LibriTTS speakers: this resulted in the generated speaker embeddings 11-20. The generated speaker embeddings were used to synthesize a set of stimuli in the target languages. The inference corpus comprised 20 phonologically rich sentences per language from conversational and general domain data from the Internet. To keep the number of samples manageable for the listening tests, some of the generated speakers have been removed, mainly those who coincide with other generated speakers or those whose synthesized samples contained considerable audible artifacts. The set of generated speakers was complemented by a baseline speaker which was generated by just averaging the embeddings of all the speakers in the dataset.

4.1. Subjective evaluation

Our models were assessed via mean opinion score (MOS) listening tests against naturalness and gender perception. For each of these evaluations, every English sample was rated by 12 unique participants (5 US & GB listeners, 2 CA) via crowdsourcing on Amazon Mechanical Turk (AMT) [18]. For Korean, the evaluation was conducted on-site, with 8 native expert participants. Each listening test page comprised samples of 11 different generated speakers (incl. baseline), 1 validation and 1 ground truth sample (gt). Listeners were asked to evaluate each sample on a 5-point Likert scale, while listening through headphones and being in a quiet setting. Naturalness was evaluated on a scale from “1: very unnatural” to “5: completely natural”. For gender perception, we created a custom test with 5 choices. Listeners were asked to rate how certain they are regarding the gender of the speaker in each sample, in a range from “certainly male” to “certainly female”, with the intermediate choices being “probably male”, “neither male nor female (ambiguous)” and “probably female”. The middle option thus corresponds to gender-ambiguous samples, which has been our target during experimentation.

After assembling the results, we used the controls described in [19] to exclude the submissions of potentially spurious participants and validate our results. For the gender perception evaluation, we slightly adjust the utilization of the gt control: the gender of the ground truth speaker sample is taken into account and the ratings of a page are discarded in case the male speaker sample has been rated as “probably/certainly female” and vice versa.

|        | US ENGLISH | KOREAN |
|--------|------------|--------|
|        | NATURALNESS MOS | GENDER-AMBIGUITY MOS | NATURALNESS MOS | GENDER-AMBIGUITY MOS |
| baseline | 3.42 ± 0.17 | 2.49 ± 0.18 | 4.08 ± 0.34 | 3.20 ± 0.27 |
| emb_1  | 3.19 ± 0.17 | 3.60 ± 0.17 | 4.31 ± 0.21 | 3.13 ± 0.41 |
| emb_2  | 3.20 ± 0.17 | 3.49 ± 0.17 | 4.38 ± 0.22 | 3.67 ± 0.44 |
| emb_3  | 2.90 ± 0.20 | 3.70 ± 0.16 | 3.50 ± 0.22 | 3.33 ± 0.44 |
| emb_5  | 3.15 ± 0.17 | 3.56 ± 0.17 | 4.12 ± 0.29 | 3.40 ± 0.45 |
| emb_6  | 3.37 ± 0.16 | 2.48 ± 0.18 | 3.96 ± 0.27 | 3.07 ± 0.43 |
| emb_7  | 2.92 ± 0.19 | 2.82 ± 0.18 | 4.04 ± 0.29 | 2.33 ± 0.35 |
| emb_8  | 3.19 ± 0.18 | 3.13 ± 0.17 | 4.08 ± 0.26 | 3.27 ± 0.43 |
| emb_11 | 3.83 ± 0.14 | 2.30 ± 0.20 | 3.96 ± 0.23 | 3.40 ± 0.36 |
| emb_15 | 2.98 ± 0.17 | 2.72 ± 0.15 | 4.38 ± 0.24 | 4.20 ± 0.32 |
| emb_16 | 3.03 ± 0.18 | 3.59 ± 0.16 | 4.35 ± 0.21 | 4.60 ± 0.25 |
| gt     | 4.70 ± 0.07 |         | 5.00 ± 0.0 |         |

Fig. 4: English MOS results of naturalness and gender perception

Fig. 5: Korean MOS results of naturalness and gender perception

4.2. Results

We obtained results for 11 generated speaker embeddings including our baseline. In Fig. 4 we display the results of the formal evaluation conducted in English, after excluding pages with unreliable responses according to our controls. In total, 32,149 ratings were analyzed for naturalness and 35,906 for gender perception. The first two columns provide information about the naturalness MOS score of each generated speaker and its 95% confidence interval (CI). The next columns relate to the perceived gender of the generated speakers. The mini-chart at the last column of the table shows in more detail how the listeners’ judgments regarding the gender were distributed among the different options. As expected, the naturalness of the generated speakers is lower than the real ground-truth speakers, but in most cases it remains high enough for most practical applications. The naturalness of the baseline speaker is quite high, which can partly be attributed to the fact that its embedding resides towards the center of the embedding space; a position that may be advantageous in various respects. However, the baseline’s gender has been perceived as male. Various generated speakers present similar or higher naturalness compared to the baseline, while 3 present significantly higher gender ambiguity. These generated speakers are indicated by a black square marker at the left of the corresponding line.

When evaluating the Korean generated speakers (Fig. 5), the perceived naturalness is notably higher. This can be attributed to the nature of the Korean subset of the data, which comprises solely proprietary and high quality recordings. Additionally, the ratings were submitted by experts, who may have been more focused to the gender perception task or more forgiving. The baseline is close to gender ambiguity but tends to be perceived as female, while our sampling approach has generated 2 speakers rated as more gender-ambiguous. Nonetheless, due to the smaller size of this test (5,317 scores for naturalness and 5,941 for gender) the results are not significant.

5. CONCLUSIONS AND FUTURE WORK

We have proposed a method for generating non-existent gender-ambiguous voices of satisfactory quality from binary-gendered data, by systematically sampling on the speaker embedding space of a multi-speaker Tacotron model. We have shown that our method generates speakers that outperform a simple baseline in both English and Korean experiments. In future work, we plan to experiment further and form a better understanding of the parameters that affect the quality and adequateness of the sampled speaker embeddings, such as the quality of the data and the language of the nearby ground truth speakers.
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