SCALABLE MULTILINGUAL FRONTEND FOR TTS

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ABSTRACT

This paper describes progress towards making a Neural Text-to-Speech (TTS) Frontend that works for many languages and can be easily extended to new languages. We take a Machine Translation (MT) inspired approach to constructing the frontend, and model both text normalization and pronunciation on a sentence level by building and using sequence-to-sequence (S2S) models. We experimented with training normalization and pronunciation as separate S2S models and with training a single S2S model combining both functions.

For our language-independent approach to pronunciation we do not use a lexicon. Instead all pronunciations, including context-based pronunciations, are captured in the S2S model. We also present a language-independent chunking and splicing technique that allows us to process arbitrary-length sentences. Models for 18 languages were trained and evaluated. Many of the accuracy measurements are above 99%. We also evaluated the models in the context of end-to-end synthesis against our current production system.

Index Terms— speech synthesis, machine learning

1. INTRODUCTION AND RELATED WORK

Text-to-Speech synthesis has made tremendous progress over the last twenty or so years, above all in terms of naturalness of the output voice. For an overview see [1]. Most recently synthesis quality has improved due to innovative Machine Learning (ML) techniques such as WaveNet [2]. It is relatively straightforward to apply these approaches to different languages.

There has also been steady progress in terms of the frontend (FE) – normally considered to be the part of a TTS system that converts input text to a phonetic representation. There are several reasons why this is a harder problem than backend waveform generation. In part it is because designing a frontend is an intrinsically more knowledge-based task. Some successful examples of multilingual synthesis include [3], [4], [5].

For a number of years Weighted Finite State Transducer solutions (WFSTs) were very popular. This approach [5], [6] is essentially a sophisticated rule-based approach. Using WFSTs requires a knowledge of linguistics and also the ability to write formal grammars that then get compiled into WFSTs.

More recently, work has focused on more general data-driven ML approaches. Several recent systems are capable of learning directly from character input [2], [7], [8], [9], [10]. The challenge for End-to-End (E2E) approaches is to have enough training data to train a high quality system.

In terms of text normalization see e.g. [11], where the authors propose a system using a large parallel corpus to train models for various recurrent neural network (RNN) architectures. They found it necessary to add a FST-based post-filter to achieve the required accuracy. Other hybrid methods have also been proposed [12]. In [13], the use of convolutional neural networks (CNNs) for text normalization was examined. In [14] the authors examine aspects of text normalization in the context of MT and using byte pair encoding (BPE) for subword units.

This paper describes our research, where the main idea is to treat the whole frontend as one or more S2S tasks in a very general way. We elaborate on this in the following sections.

2. SYSTEM

The aim of our work is to model both normalization and pronunciation (sometimes called grapheme-to-phoneme (G2P)) to provide all the information necessary for input to the TTS backend – e.g. WaveNet. The input is raw text in an unnormalized form, and the output is a sequence of phonemes along with some additional information.

We regard the frontend as exactly equivalent to a translation task and employ the tools of MT directly. The task of building a frontend can be considered as either one or two translation tasks, depending on how the problem is structured.

If configured as two tasks we find it convenient to divide the problem into normalization and pronunciation, since it fits in well with how the problem is conventionally structured.

To a first approximation local context is most important for clarifying the normalization of a character sequence, or the pronunciation of a word. However, in our case we find it useful to consider whole sentences (1) for the practical reason that the MT infrastructure is focused on sentences and (2) there are some long term dependencies that can guide normalization and pronunciation, for example related to given vs. new distinctions [15].

Pronunciations are also generated from the translation sentence context, rather than from a lexicon. We use parallel
data in the form of pairs of sentences, with input in the form of normalized words, and the output in terms of phonemes. We then train a S2S model based on that data, and use the model to generate pronunciations for our input sentences (or words). For our experiment we use only parallel data, with no extra helper knowledge, and the only data supplied at training time is input and output examples (training set and development set). In the one-model case, the modeling must take account of both sets of challenges, normalization and pronunciation.

2.1. Transformer Model Architecture

We use the Fairseq [16] implementation of Transformer [17] sequence-to-sequence models to build all our models. The architecture of a Transformer model is shown in Fig. 1. The model consists of two components: an encoder and a decoder. Each contains of set of stacked layers composed primarily of multi-head attention sublayers that feed into feedforward sub layers. The attention sublayers in the encoder only attend to the input sequence (and features derived from it). The decoder can attend to the partial sequence of generated tokens and is masked to prevent it from attending to future tokens. The decoder also has attention on the output of the encoder stack. The heads in an attention sublayer are able to form independent representations that may attend to different positions.

The architecture we used had 6-layer encoder and decoder stacks, 8 attention heads, embedding dimension 512, and feedforward network embedding dimension 2048. Training is performed on a parallel corpus using stochastic gradient descent (SGD).

2.2. Byte Pair Encoding

We follow the MT practice of preprocessing the training data. Byte Pair Encoding (BPE) in the context of dealing with rare words is described by Sennrich et al. [18]. BPE encodes the most frequent character bigrams as unseen unigrams and the process is repeated until a stopping point is reached. BPE is a form of data compression. It is also a way to deal with out-of-vocabulary words by attempting to break them down into component parts. Table 1 shows an example of the BPE-processed data. The @@ symbol is used to indicate where BPE has divided a word into subwords. In [14] there is a detailed analysis of using BPE and different data sizes for a normalization task. BPE encoding is used for all the models we build.

2.3. Dual model

For the dual model case we divide the problem of translating text into two parts (1) normalization (with or without punctuation) and, (2) pronunciation.

The system is trained on several million sentences in parallel (details below). Training is carried out using standard Fairseq recipes, with a training set, validation set and test set.

2.4. Single model

For the single model case we combine normalization and pronunciation into one model. Training is carried out in a similar fashion to the dual models.

2.5. Splicing

For either the single or dual model case it is important to have a strategy for dealing with arbitrarily long sentences. We take a straightforward approach of dividing longer sentences into multiple overlapping parts of length 25 words, with an overlap of 10 words, without regard to sentence boundaries or syntax.

Table 1. Effect of BPE on data

| Input | Output |
|-------|--------|
| Hello | World |

![Fig. 1. Neural machine translation architecture](image-url)
To produce the final output we align overlapping output sequences by maximizing the word level agreement in the overlap.

3. EXPERIMENTS

To test how easy it was to bring up a FE for a new locale, we built models for 18 different locales and compared model performance across locales.

For each locale our training data consists of roughly 5 million sentences. The data was collected by web crawling and processed to extract sentences. No specific limitations were put on the form of these data.

Next, these sentences were input to a working production synthesizer and intermediate and final processed forms of the data were extracted to give a database of parallel sentences in “unnormalized”, “normalized” and “phone sequence” forms.

| Model      | Input       | Output       |
|------------|-------------|--------------|
| Normalization | unnormalized | normalized   |
| Pronunciation | normalized  | phone sequence |
| Combined   | unnormalized | phone sequence |

Table 2. Source and Target Data for each S2S Model

The source and target data for each type of model is shown in Table 2. Each of these sets formed the initial basis for training a model. From the data sets described, and for each locale of interest we then trained a model using the method outlined in Section 2.1 above. For the specific models described here, no tokenization was carried out on the data prior to the BPE step. We used a joint BPE, with a codebook of 32k pairs, and 16-GPU Fairseq configuration in our experiments. We held out 10,000 sentences for validation, and 10,000 sentences for testing. None of the validation or test sentences were contained in the training data.

Speed was not considered here. In general generating an encoding can be somewhat slow, but encoding and decoding thereafter is not expensive.

3.1. Listening tests

Testing the output quality of the FE models in a complete synthesis system presents certain complexities. First, text differences compared with the teacher system are infrequent and usually minor. Second, the models form part of a Neural E2E system, with a Neural Backend (BE). When comparing with a Unit Selection production system any listening tests will inevitably reflect the influence of the BE. Nevertheless, to find out whether the FE models are able to provide all the information necessary for a production scenario we ran listening tests comparing the completely E2E system with the production system for several locales.

4. RESULTS

4.1. Accuracy results

Two measures were used to assess accuracy on the held out test set: BLEU [19] and chrF3 [20].

We observed that given a high-quality database the training will reproduce the patterns in the data to a high degree of accuracy.

Results for the dual model case are given in Table 3. Generally the accuracy was lower, but still reasonable for most synthesis cases. For longer sentences the test outputs are created by splicing multiple shorter outputs.

Accuracy variation among locales may be reflective of the structure of the language or the extent to which the process (BPE and Fairseq) aligns with language. We did observe some correlation with the quality of the training data.

| Locale   | Normalization BLEU | Normalization chrF3 | Pronunciation BLEU | Pronunciation chrF3 |
|----------|---------------------|----------------------|--------------------|----------------------|
| en-US    | 99.69               | 0.9991               | 97.09              | 0.9926               |
| es-ES    | 99.79               | 0.9990               | 99.88              | 0.9996               |
| it-IT    | 99.80               | 0.9994               | 99.71              | 0.9991               |
| pt-PT    | 99.85               | 0.9993               | 99.68              | 0.9992               |
| fr-FR    | 99.70               | 0.9991               | 99.52              | 0.9985               |
| sv-SE    | 99.10               | 0.9934               | 99.34              | 0.9970               |
| nl-NL    | 98.13               | 0.9855               | 98.62              | 0.9925               |
| en-AU    | 99.60               | 0.9870               | 98.91              | 0.9882               |
| de-DE    | 99.80               | 0.9877               | 95.87              | 0.9895               |
| ru-RU    | 99.00               | 0.9942               | 99.10              | 0.9964               |
| da-DK    | 97.07               | 0.9915               | 97.94              | 0.9894               |
| en-IN    | 99.15               | 0.9969               | 99.51              | 0.9974               |
| nb-NO    | 93.93               | 0.9808               | 96.22              | 0.9853               |
| en-ZA    | 98.20               | 0.9855               | 98.02              | 0.9865               |
| en-IE    | 97.72               | 0.9810               | 97.65              | 0.9833               |
| tr-TR    | 94.20               | 0.9765               | 98.14              | 0.9853               |
| en-GB    | 83.66               | 0.9005               | 99.56              | 0.9975               |
| pt-BR    | 79.10               | 0.6585               | 95.86              | 0.9673               |

Table 3. Testing Accuracy – dual model

For the single model case refer to Table 4. Generally the accuracy was lower, but still very reasonable for most synthesis cases. This table also illustrates the significant performance boost achieved by using the splicing technique.

We analyzed modeling errors, particularly for the text normalization component. For en-US, of our 10,000 test sentences, 127 differed from the baseline reference. We divided those 127 into the categories shown in Table 5. None of the errors appeared completely random, most of the differences were minor. Cases labeled “punctuation”, for example often involved hyphens being absent or present. Cases labeled “2nd lang” contained substantial amounts of other language text.

Some example differences are shown in Table 6. Some of the differences appear to be because the MT generalizes
Table 4. Testing Accuracy – single model, unspliced and spliced

| Locale   | Combined BLEU | chrF3 | Combined, Spliced BLEU | chrF3 |
|----------|---------------|-------|------------------------|-------|
| de-DE    | 92.01         | 0.9484| 94.82                  | 0.9782|
| en-US    | 92.94         | 0.9428| 96.84                  | 0.9822|
| es-ES    | 91.51         | 0.9246| 99.54                  | 0.9969|
| nl-NL    | 94.42         | 0.9509| 97.41                  | 0.9826|
| ru-RU    | 94.46         | 0.9558| 98.48                  | 0.9919|
| sv-SE    | 97.39         | 0.9789| 98.41                  | 0.9891|

Table 5. Breakdown by type of differences in en-US text normalization

| Instances | Type       | Percentage |
|-----------|------------|------------|
| 21        | better     | 16%        |
| 11        | equal      | 9%         |
| 39        | punctuation| 31%        |
| 4         | 2nd lang   | 3%         |
| 52        | worse      | 41%        |

Table 6. Examples of differences in en-US text normalizations

| Locale      | Type                        | Percentage |
|-------------|-----------------------------|------------|
| de-DE       | 11.40AM IST                 |            |
| en-US       | eleven forty AM ist         |            |
|             | eleven forty AM Irish summer time |     |
|             | (A Y uu u uge amount of articles?), |            |
|             | A y uu u uge amount of articles.|            |
|             | A y uu u uge amount of articles.|            |
|             | a wind that stiffened to 70 kmh by lunch.| |
|             | a wind that stiffened to seventy K M H by lunch |     |
|             | a wind that stiffened to seventy kilometers per hour by lunch | |

Table 7. Partial summary of listening experiments, focusing on Neural E2E system

4.2. Listening test

We also incorporated the models as part of a full TTS pipeline, ran them end to end and performed listening tests. The S2S FE components gave essentially identical results for these real world testing cases. (The cases are generally less challenging than our held out test set).

Table 7 shows partial results from various subjective listening tests measuring naturalness for an E2E system compared to a production system. Any quality improvements are reflective of the BE.

Table 5. Breakdown by type of differences in en-US text normalization

Table 6. Examples of differences in en-US text normalizations

Table 7. Partial summary of listening experiments, focusing on Neural E2E system

5. CONCLUSIONS

The main contributions of this paper is a general framework where S2S models can replace the FE of an existing rule-based TTS. The existing system is used as a teacher to help train the models, providing normalized and pronunciation forms for a large database of unnormalized sentences. These parallel data are then used as input data for S2S training.

For the configurations we studied, the dual model gives the better performance, however the single model is smaller overall and has better processing characteristics, and in terms of quality is comparable to the dual model.

Our approach to pronunciations does not rely explicitly on a lexicon or isolated word pronunciation modeling, but instead provides a general language-independent framework for dealing with pronunciations in context.

For inference we introduced the language-independent idea of cutting input text into chunks and splicing the outputs back together. This both improved the accuracy of our models and allows the synthesis of arbitrary-length sentences.

To demonstrate the scalability and generality of our approach, we presented a large-scale study where we trained models for 18 locales and measured high accuracies. We also tested our models in a full synthesis context against a production system. Under testing, the FE models were found to be robust and accurate.
6. REFERENCES

[1] Paul Taylor, *Text-to-Speech Synthesis*, Cambridge University Press, 2009.

[2] Aáron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew W. Senior, and Koray Kavukcuoglu, “WaveNet: A generative model for raw audio,” *CoRR*, vol. abs/1609.03499, 2016.

[3] Susan Hertz, Rebecca J. Younes, and Nina Zinovieva, “Language-universal and language-specific components in the multi-language eti-eloquence text-to-speech system,” 08 1999.

[4] Richard Sproat, Ed., *Multilingual Text-to-Speech Synthesis: The Bell Labs Approach*, 1997.

[5] Richard Sproat, “Multilingual text analysis for text-to-speech synthesis,” 1996, vol. 2(4), p. 369380.

[6] Brian Roark, Richard Sproat, Cyril Allauzen, Michael Riley, Jeffrey Sorensen, and Terry Tai, “The openGrm open-source finite-state grammar software libraries,” Association for Computational Linguistics, 2012, p. 6166.

[7] Yuxuan Wang, R. J. Skerry-Ryan, Daisy Stanton, Yonghui Wu, Ron J. Weiss, Navdeep Jaitly, Zhongheng Yang, Ying Xiao, Zhifeng Chen, Samy Bengio, Quoc V. Le, Yannis Agiomyrgiannakis, Rob Clark, and Rif A. Saurous, “Tacotron: A fully end-to-end text-to-speech synthesis model,” *CoRR*, vol. abs/1703.10135, 2017.

[8] Jonathan Shen, Ruoming Pang, Ron J. Weiss, Mike Schuster, Navdeep Jaitly, Zhongheng Yang, Zhifeng Chen, Yu Zhang, Yuxuan Wang, R. J. Skerry-Ryan, Rif A. Saurous, Yannis Agiomyrgiannakis, and Yonghui Wu, “Natural TTS synthesis by conditioning wavenet on mel spectrogram predictions,” *CoRR*, vol. abs/1712.05884, 2017.

[9] Sercan Ömer Arik, Mike Chrzanowski, Adam Coates, Greg Diamos, Andrew Gibiansky, Yongguo Kang, Xian Li, John Miller, Jonathan Raiman, Shubho Sengupta, and Mohammad Shoeybi, “Deep voice: Real-time neural text-to-speech,” *CoRR*, vol. abs/1702.07825, 2017.

[10] Jose Sotelo, Soroush Mehr, Kundan Kumar, João Felipe Santos, Kyle Kastner, Aaron C. Courville, and Yoshua Bengio, “Char2wav: End-to-end speech synthesis,” in *ICLR*, 2017.

[11] Richard Sproat and Navdeep Jaitly, “RNN approaches to text normalization: A challenge,” *CoRR*, vol. abs/1611.00068, 2016.

[12] Ernest Pusateri, Bharat Ram Ambati, Elizabeth Brooks, Ondrej Plátek, Donald McAllaster, and Venki Nagesha, “A mostly data-driven approach to inverse text normalization,” 2017, p. 27842788.

[13] Sevinj Yolchuyeva, Géza Németh, and Bálint Gyires-Tóth, “Text normalization with convolutional neural networks,” *International Journal of Speech Technology*, p. 112, 2018.

[14] Courtney Mansfield, Ming Sun, Yuzong Liu, Ankur Gandhe, and Bjorn Hoffmeister, “Neural text normalization with subword units,” in *NAACL-HLT*, 2019, pp. 190–196.

[15] Julia Hirschberg, “Pragmatica and intonation,” 2008.

[16] Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli, “fairseq: A fast, extensible toolkit for sequence modeling,” *CoRR*, vol. abs/1904.01038, 2019.

[17] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin, “Attention is all you need,” *CoRR*, vol. abs/1706.03762, 2017.

[18] Rico Sennrich, Barry Haddow, and Alexandra Birch, “Neural machine translation of rare words with subword units,” *CoRR*, vol. abs/1508.07909, 2015.

[19] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu, “BLEU: a method for automatic evaluation of machine translation,” ACL, July 2002, pp. 311–318.

[20] Maja Popović, “chrF: character n-gram F-score for automatic MT evaluation,” Association for Computational Linguistics, 2015, p. 392395.