TOWARDS LANGUAGE MODELLING IN THE SPEECH DOMAIN USING SUB-WORD LINGUISTIC UNITS

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ABSTRACT

Language models (LMs) for text data have been studied extensively for their usefulness in language generation and other downstream tasks. However, language modelling purely in the speech domain is still a relatively unexplored topic, with traditional speech LMs often depending on auxiliary text LMs for learning distributional aspects of the language. For the English language, these LMs treat words as atomic units, which presents inherent challenges to language modelling in the speech domain. In this paper, we propose a novel LSTM-based generative speech LM that is inspired by the CBOW model and built on linguistic units including syllables and phonemes. This offers better acoustic consistency across utterances in the dataset, as opposed to single melspectrogram frames, or whole words. With a limited dataset, orders of magnitude smaller than that required by contemporary generative models, our model closely approximates babbling speech. We show the effect of training with auxiliary text LMs, multitask learning objectives, and auxiliary articulatory features. Through our experiments, we also highlight some well known, but poorly documented challenges in training generative speech LMs, including the mismatch between the supervised learning objective with which these models are trained such as Mean Squared Error (MSE), and the true objective, which is speech quality. Our experiments provide an early indication that while validation loss and Mel Cepstral Distortion (MCD) are not strongly correlated with generated speech quality, traditional text language modelling metrics like perplexity and next-token-prediction accuracy might be.

Index Terms— Language Modelling, Speech Synthesis

1. INTRODUCTION

From traditional n-gram models to more recent LSTM and transformer based neural models, language models (LMs) in the text domain have been explored extensively [1, 2, 3, 4]. Their performance on language modelling tasks as measured by token prediction accuracy and perplexity, and on downstream natural language processing tasks such as question answering, natural language inference, and sentiment analysis among others, have been the subject of several studies including some that have even helped develop an understanding of how well these models scale with the amount of training data, and the number of model parameters [5]. Studies that probe text neural language models for real world knowledge have established methods for understanding what information is stored in these LMs and at what point during training they begin to know it [6, 7, 8]. With GPT-3 [4], generative language models have crossed the 100 billion parameter mark and can produce fluent natural language text that is difficult to distinguish from human generated text. In general, it may be said that contemporary text LMs are both, good representation learners, and language generators.

Language models in the speech domain, however, have been explored relatively less. Models such as wav2vec [9] and Mockingjay [10] show state-of-the-art performance on word- and phoneme-error-rate, and other downstream tasks such as speaker identification and sentiment analysis. While these are good representation learners, they are not speech synthesizers. On the other hand, Text-To-Speech (TTS) models such as Tacotron [11], are just that, and therefore not pure speech language models. “Textless NLP” models such as Slow AutoEncoders (SlowAEs) [12] and the Generative Spoken Language Model (GSLM) [13] are amongst the first that attempt to build language models in the speech domain directly and purely from raw speech (waveform). However, these models use hundreds or thousands of hours of speech data, and models whose parameters number in the hundreds of millions, or billions - both several orders of magnitude greater than our proposed method. Further, unlike our method that uses linguistic units, they use entire utterances of raw speech as input, limiting applications to single language systems.

Generative speech models use the raw speech waveform, or melspectrograms generated from raw speech as their input, and a single frame as the computational unit of speech. Single melspectrogram frames contain about 5-10ms of speech or less, which is smaller than the average length of a phoneme in English. This short length prevents a single frame from containing much inherent linguistic structure, and leads to a large variation in frames across different parts of the entire melspectrogram. Instead, using linguistic units such as phonemes and syllables, offers more consistency in structure across the utterance. As a first step towards linguistically
grounded speech LMs, we propose a simple LSTM based encoder-decoder model that babbles. In our experiments, we show that using auxiliary information such as articulatory linguistic features, or embeddings from text LMs built on the same linguistic units (phonemes or syllables) can improve synthesis quality considerably. We also find that multi-task learning objectives that encourage the model to capture these linguistic features help improve synthesis quality.

Throughout the paper, we discuss several well known, but poorly documented challenges of training speech synthesis models such as the disagreement between generated speech quality and the supervised learning objective, which consequently make the use of learning curves unreliable in decisions concerning duration of training and objectively identifying better models.

2. RELATED WORK

Language Modelling in Text In their most simple definition, language models are statistical models that can assign a probability score to a given sequence of tokens \[14\]. Further, and particularly important to our work, language models that are trained in a purely auto-regressive manner (with left context only) can be used to generate language. Early recurrent neural network language models were already quite successful in outperforming traditional n-gram based language models \[1\] measured by objective metrics such as perplexity and accuracy of next-token prediction. The skip-gram and CBOW models presented in \[2\] serve as the baseline architecture that we replicate in the speech domain. Transformer based language models such as BERT \[3\], and RoBERTa \[15\] make use of bi-directional encodings and cannot be considered true language models in this sense. The use of bi-directional context inhibits their use in generating language.

Speech Synthesis Though Variational Autoencoders (VAE) and Generative Adversarial Networks (GANs) have been used in speech synthesis \[16\], they are not language models in that they do not possess any of the aforementioned LM properties - specifically, being conditioned on the left context, and being able to predict the next token in speech. Text-to-Speech models are closer to being language models, but are not pure speech language models. Modern TTS models are also not strictly left-to-right conditioned because of their use of Transformer \[17\] style bi-directional architectures. Several TTS models now use auxiliary features from text LMs to enhance the quality of generated speech. In \[18\] the use of auxiliary embeddings from a BERT text language model is reported to produce significant improvement in the quality of generated speech. The cause for this improvement and the precise information these auxiliary features contain is not investigated. Continuing in this line of research, we experiment with auxiliary features from two text LMs - including one non-Transformer model - and study their effect on the quality of synthesised speech. Our findings indicate that the accuracy and perplexity of these auxiliary models plays a significant role in the quality of speech produced.

The use of Sub-word Linguistic Units The choice of the fundamental unit for language modelling in speech is
not as straightforward as it is in the text domain where languages like English are generally tokenized on whitespace. In speech, sub-word models are more closely investigated in languages such as Mandarin [19] although applications are mostly limited to ASR, and do not include synthesis. [20] argues for the use of sub-word models in Automatic Speech Recognition because of their advanced ability to handle large vocabulary corpora with many low-frequency tokens. Sub-word units also provide a more consistent acoustic representation in comparison to entire words or single melspectrogram frames. Particularly, the use of phonemes allows us to work with a limited vocabulary, with only 39 phonemes in the English CMU Phoneme Dictionary. The use of syllables, which in our definition always contain a central vowel, also offer consistency in the acoustic domain.

Articulatory features Another challenge in speech processing is the great variation in the manner of articulation of phones, which is also often context dependent.

Previous work has argued for representing speech as "multiple parallel streams of information". Each stream provides information about different articulatory features of the speech segment such as being voiced or unvoiced. [21] presents a novel toolkit for representing IPA speech segments with 22 articulatory features. In their experiments, the authors report the use of these articulatory features in conjunction with word-vector based methods achieves superior performance on NLP tasks such as Named Entity Recognition, as compared to word-vector methods alone. The Panphon toolkit proposed in [21] converts IPA speech segments into 22 articulatory features, and significantly improves performance over word-vector based methods, when used as auxiliary features in conjunction with these dense-vector representations. In our experiments, we make use of these articulatory features as auxiliary inputs to our speech LM, as well as in a multitask setting in which the latent representation from our LSTM-encoder is used to predict these features. This is discussed in further detail in section 4.

Speech quality assessment A well known problem in speech synthesis is the lack of objective methods of evaluating the quality of synthesised speech. From observations made by training several models (with reasonable exploration of the hyperparameter space) it is also clear that there is no strong correlation between the optimization objective used to train speech synthesis models and the quality of synthesised speech. MOS is a widely used metric but given its subjective nature it is impossible to make direct comparisons between results from different studies without re-implementing the proposed models, and conducting a fresh round of human evaluation. We make use of Mel-Cepstral-Distortion (MCD) in our experiments and also evaluate the latent representations of our model on downstream language modelling tasks such as next token prediction and report the correlation between model performance on these tasks and MOS.

### 3. Dataset

We use the LJSpeech dataset for all models and experiments in the speech domain. This dataset contains 24 hours of read English speech from audio-books and is part of the LibriVox project. For phoneme-level LMs, each utterance is split into constituent phonemes according to alignments generated by [todo]. For syllable-level LMs, we first define a syllable as a unit that contains at least a vowel, and optionally a pre-vowel and post-vowel made up of one or more consonants. Syllable alignments are generated by [todo] - Syllables longer than 250ms, phonemes longer than 150ms, and all silences are removed from the dataset. This ultimately leaves us with approximately 18 hours of speech.

Note that we convert all of our speech data into melspectrogram representations of the waveform. For articulatory linguistic features for syllables we use the Panphon toolkit [21] that maps phonemes to 22 subsegmental articulatory features. When the pre- and post-vowel contain more than one consonant, we combine their representations using max-pooling to obtain a single feature vector for the pre-vowel, and the post-vowel. Finally, we concatenate the resulting feature vectors of the pre-vowel, vowel, and post-vowel to obtain a single 66-dimensional vector.

For our text LMs that are used to provide auxiliary information to the speech LM, we use a subset of the English Wikipedia dataset that contains approximately 30 million tokens. Note that since we want to use the same units for the
speech and text LMs, this text is also syllabified, or converted to phonemes, in a similar manner to the utterances in the LJSpeech dataset. Table 1 contains examples of syllabified text from the LJSpeech dataset.

4. EXPERIMENTS

A simplified diagram of our model(s) is shown in Figure 1. Below, we describe the details of all our models and experiments.

**Pure Speech Language Model** As our first approximation, we construct a simple LSTM-based encoder-decoder language model (Synthesis-only model in Table 2) inspired by the CBOW model [2]. For this model to be a true language model, we only provide it with the left context, and frame the problem to predict the next unit given this context. In our experiments, we find 4 units (syllables or phonemes) of context to be optimal. The encoder LSTM first extracts 256-dimensional latent representations from the melspectrogram of each of the 4 context units independently, $v_i$. These latent representations are then concatenated into a single 1024-dimensional vector ($z$) and used as an input to the decoder LSTM to predict the melspectrogram frames of the next syllable. The decoder thus models the auto-regressive LM objective $p(y|z)$, where $y$ is the next unit to be predicted given the context $z$. Loss is computed as the Mean Squared Error between the predicted and the ground truth melspectrogram.

**Multitask Learning Objectives** In order to encourage the model to produce more diverse sounding units without using more speech data, we use an auxiliary objective to predict the Panphon representation of the next unit and train in a Multitask Learning setting. Concretely, the 1024-dimensional latent representation is additionally used as input to an auxiliary classifier that predicts the 66-dimensional Panphon vector of the next syllable. We treat this as binary classification, and the loss is computed as an average of binary cross entropy over 66 independent variables. In Table 2 these models are listed as MTL (Panphon).

**Auxiliary Features** This method is already widely used in several state of the art Text-to-Speech systems [18]. For this, we first train two types of text language models on our Wikipedia text dataset. Note that the text in this dataset has been preprocessed identically to the transcripts of the LJSpeech dataset for the respective sub-word linguistic unit type. We experiment with two types of text language models - an LSTM language model whose embedding matrix is initialised using a word2vec model trained on the same text data, and transformer based RoBERTa model [15]. Note that since our vocabulary no longer contains English words, and instead is comprised of phonemes or syllables, we train the RoBERTa model and its corresponding tokenizer from scratch. The representations from these models, $z_{text}$, are then concatenated to the latent representation $z$ extracted by the speech LSTM-encoder and fed into the decoder. We use a fixed embedding size of 768 for the text LMs, therefore, the new latent representation $z'$ is a 1792 dimensional vector. The weights of the text language models are frozen after training and are not updated when training the speech language model.

Finally, since there is no comparable baseline method, to the best of our knowledge, that performs speech language modelling similar to our method, we suggest the use of a “top-line” instead. This is meant to represent the highest quality of speech that a sub-word linguistic unit based speech language model can generate when given the ground-truth linguistic information about the next unit to be predicted. We model this by providing the Panphon representation vector as auxiliary information and concatenating it to the extracted latent representation of the context speech units, $z$. Naturally, such a setting is not possible in a real world scenario where the next unit is unknown and to be predicted. However, we find it a good demonstration of the potential of using articulatory features of sub-word units. This model is listed as “Auxilliary (Top-line)” in Table 2.

5. DISCUSSION AND ANALYSIS

In this section we make several observations from the babbling speech generated by our various models and provide insights into the observed phenomena.

**Observation 1** Using the syllabified LJSpeech dataset directly results in a low diversity in the generated speech.

Our first approximation (Pure Speech LM) used the LJSpeech dataset that was preprocessed only to remove pauses and syllables or phonemes that were exceptionally short or long. However, the syllable distribution, in this dataset, shown in Figure 2 is highly skewed, with “ax” and “dhax” together making up about 10% of the dataset which has approximately 5000 syllables. The generated samples contain repetitive speech that resembles the “ax” sound...
Observation 2: The latent representation of the Pure Speech LM lacks discriminative information about the predicted token.

To investigate whether the latent representation extracted by the LSTM-encoder contains information about the next token to be predicted, we build a post-hoc phoneme classifier. Since the vowel is central to our definition of the syllable, and since the number of phonemes (16) is significantly smaller than the number of syllables in the dataset, we hypothesise that phoneme classification is an ideal test for information contained in the latent representation. For the pure speech language model, we observe that this defaults to a majority classifier as seen from the confusion matrix in Figure 3 (a).

Observation 3: Panphon features contain important linguistic information that is useful to speech language modelling.

When the same post-hoc classifier is trained with Panphon representations directly, accuracy improves greatly, Figure 3 (b). This confirms that the Panphon features do contain important linguistic information. Guided by this observation we select the prediction of Panphon features as an auxiliary task in our multitask learning setting with the hope that it encourages more linguistic information to be captured in the latent representation that is fed into the decoder. Indeed, as seen from Figure 3 (c) there is an improvement in vowel prediction performance. This improvement can also be observed qualitatively in the mel-spectrogram in Figure 4.

Observation 4: Supervised learning loss and MCD are not well-correlated with the quality of generated speech, but language modelling metrics like perplexity may be.

A common pattern across all the models that we trained, with varying hyperparameter combinations, has been that the quality of speech monotonously increases until it plateaus. However, the validation loss follows the traditional trend of first decreasing to a minima, then gradually increasing again before also reaching a plateau. This is surprising since an improvement in the speech quality is not reflected in the training dynamics of the model. Clearly, this indicates a gap in the supervised learning objective used for speech synthesis (mean squared error) and the true objective, which is speech quality. We also compute Mel Cepstral Distortion (MCD) over ten samples generated from each of our models and report the results in Table 2. Similar to validation loss, we find MCD is not strongly correlated with speech quality either. Following from Observation 3 above, however, we find that the latent embeddings from the Top-line model perform the best at predicting the next vowel, followed by the Multitask-Learning model. This indicates that traditional text language model metrics like perplexity and next-token-prediction accuracy might be better indicators of generated speech quality. This calls for further research in better metrics that capture speech quality more closely and that can be directly optimised in training speech language models.

6. CONCLUSION

We present a novel speech language model along the lines of recent work in the textless-NLP domain. Our model uses mel-spectrogram representations and builds on top of linguistic units like syllables or phonemes, instead of using raw waveforms of complete speech utterances. With several orders of magnitude lesser data, and significantly smaller models, our model closely approximates babbling - mel-spectrograms of our generated speech show clear indication of syllabic structure being learned. The dataset we use is approximately 18 hours of single-speaker read speech, and is several orders of magnitude lesser than that used by [12] and GSLM. We leave the study of scaling laws of our speech language model to future work.

The strength of our model also lies in its high-impact ap-
application areas. In speech language pathology, for example, mis-spelling of particular phonemes and syllables are indicative of particular speech and language impairments. Sub-word language models such as ours can be used to build effective speech recognition and synthesis systems that can be used as diagnostic tools and learning aids for affected individuals [22, 23]. Our method is also useful for low resource languages. Specifically, similar to [24], the use of syllables allows to generate accented speech in a different language, such as, using a Telugu dataset to generate Telugu-sounding Marathi speech.

Through our analyses we show the capability of our different models in capturing information in their latent representations that is useful to language-modelling. Most notable is the observation that Panphon representations, which have previously proved successful in improving performance of text based natural language tasks, also show promise in the speech language modelling domain. Finally, we highlight an important research gap in speech quality assessment and show that while validation loss and MCD are not strongly correlated with MOS for our models, traditional text language modelling metrics like perplexity and next-token-prediction accuracy could be.

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8. APPENDIX

| Model                | MOS | MCD |
|----------------------|-----|-----|
| Synthesis-only       | 3.3 | 3.15|
| MTL (Panphon)        | 3.4 | 3.14|
| Auxiliary (LSTM-LM)  | 2.8 | 3.08|
| Auxiliary (RoBERTa)  | 2.9 | 3.10|
| Auxiliary (Top-line) | 3.7 | 3.13|

Table 2: Mean Opinion Score (MOS) and Mean Mel Cepstral Distortion (MCD) over 10 speech samples generated from our 5 different models.
Fig. 4: Melspectrograms generated from the various models after 6 and 12 hours of training respectively. Clearly, as training progresses, more syllabic structure emerges in the spectrograms.