

LSTM Acoustic Models Learn to Align and Pronounce with Graphemes

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Abstract

Automated speech recognition coverage of the world’s languages continues to expand. However, standard phoneme based systems require handcrafted lexicons that are difficult and expensive to obtain. To address this problem, we propose a training methodology for a grapheme-based speech recognizer that can be trained in a purely data-driven fashion. Built with LSTM networks and trained with the cross-entropy loss, the grapheme-output acoustic models we study are also extremely practical for real-world applications as they can be decoded with conventional ASR stack components such as language models and FST decoders, and produce good quality audio-to-grapheme alignments that are useful in many speech applications. We show that the grapheme models are competitive in WER with their phoneme-output counterparts when trained on large datasets, with the advantage that grapheme models do not require explicit linguistic knowledge as an input. We further compare the alignments generated by the phoneme and grapheme models to demonstrate the quality of the pronunciations learnt by them using four Indian languages that vary linguistically in spoken and written forms.

Index Terms: Acoustic modeling, grapheme, alignment

1. Introduction

Automated speech recognition (ASR) performance has seen rapid improvements in recent years. Conventional speech recognizers are comprised of four main components: acoustic, language, and pronunciation (lexicon) models, and search decoders. The acoustic and language models are statistical models that have been improved over the last few decades with newer algorithms and increased training data. In contrast, the lexicon is usually manually generated using a dictionary of human transcribed word pronunciations. Human-curated dictionaries suffer from various challenges, such as the prohibitive cost involved with acquiring pronunciations for the different dialects and accents of a language, as well as for new languages.

To address these challenges, there have been several statistical approaches aimed at automated unit and lexicon discovery from speech audio [1, 2], grapheme-to-phoneme (g2p) conversion [3] and more recently with the use of Long Short-Term Memory (LSTM) networks [4]. However, these models still need to be trained on manually curated pronunciation dictionaries.

Grapheme models have also been used to address the challenges of acquiring lexica. For instance, in the iARPA-sponsored BABEL program that focused on the rapid development of ASR and keyword-spotting systems for low resource languages, graphemic systems were widely used [5–9], and it was shown that graphemic ASR systems can yield similar performance to the phonemic systems. In this paper, we aim to

build graphemic speech recognizers with *large scale speech data for high-resource languages* but without the use of lexica.

LSTM cells can model varying contexts (“memory”) and have been successful in a number of sequence prediction tasks [10–12]. In ASR, grapheme LSTMs have been used with the Connectionist Temporal Classification (CTC) loss [13, 14] in [15–17], and with lattice-free MMI objective in [18] to obtain competitive performance in speech recognition. Encoder-decoder based grapheme models [10, 12] doing end-to-end (E2E) speech recognition have also been proven to be competitive with conventional models.

As these models become increasingly popular, an understanding of the alignment they produce between speech frames and linguistic elements such as phonemes, graphemes, or words is important for not only ASR but also tasks such as keyword spotting [19, 20], grapheme-to-phoneme conversion [21], captioning [22, 23] and speech synthesis [24]. While graphemic models have been studied in the traditional HMM-GMM framework [25, 26], the literature does not offer us a thorough understanding of the quality of graphemic alignments produced by these models. Recently [27] explored the use of word alignments produced by direct acoustics-to-word models trained with a cross-entropy objective. However, word-level modeling of speech is problematic due to out-of-vocabulary (OOV) issues [22, 28], which we can avoid by using graphemes instead.

Motivated by the success of graphemic LSTM neural networks, in this paper we study their ability to implicitly learn alignments and pronunciations while being trained to recognize speech. *Using four Indian languages consisting of 2K-18K hours of speech data, and with varying phonetic orthography and accents, we demonstrate the ability of LSTMs to align grapheme sequences with spoken audio.* Our cross-entropy (CE) training of these models allows alignment quality to be explicitly optimized as part of the training objective, resulting in high-quality acoustic-to-grapheme alignments. Furthermore, we analyze and compare the quality of alignments between the grapheme and phoneme models, and attempt to *understand the pronunciation-modeling capability of these graphemic LSTMs.* To the best of our knowledge, this is one of the first pieces of work on large scale data that specifically attempts to interpret the pronunciations and alignments learnt by graphemic neural networks.

Our proposed training methodology also *allows flat starting, and is purely data-driven.* Therefore it offers the benefit of creating speech recognizers for new languages, an use-case where grapheme models have shown the biggest potential. Our grapheme acoustic models (AMs) trained with large-scale speech data, achieve similar WERs in speech recognition to that of phoneme models while avoiding the use of manually-curated lexicons. Additionally, due to their *ability to be combined with conventional speech-modeling elements such as language models and finite-state transducer (FST) decoders, they offer a straightforward launch path,* and are thus advantageous

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over grapheme-output E2E models.

2. Methods

In this section, we describe the graphemic lexicon and the GMM-based graphemic alignments used to flat start the graphemic LSTM acoustic models.

2.1. Graphemic Lexicon

A graphemic lexicon is a mapping between graphemes and words with a special “<space>” grapheme acting as the word boundary. The set of graphemes for a language are generated by enumerating the characters empirically observed in the training data, after removing the very rare graphemes (<10 occurrences) and those without any clear acoustic realization (such as emojis). Utterances containing the excluded graphemes are dropped from the training data. The number of graphemes used in each language is presented in the first column of Table 1.

2.2. LSTM and Cross-Entropy Loss

LSTMs can model long-range temporal dependencies, which make them particularly suited for ASR. In real-time streaming ASR applications such as voice search, we prefer uni-directional over bi-directional LSTM [15] because the former is able to perform recognition in an online fashion. The LSTM AM takes the current feature sequence $\mathbf{x} = (x_1, \dots, x_T)$ as inputs and estimates the output posteriors over a pre-defined label set, $\mathbf{l} = (l_1, \dots, l_T)$. The LSTM parameters can thus be estimated by maximizing the cross-entropy (CE) loss [29] on all frames of input utterance \mathbf{x} with its corresponding frame-level alignment \mathbf{l} .

$$L_{CE} = - \sum_{(\mathbf{x}, \mathbf{l})} \sum_{l_t, t} \delta(l_t, l_t) y_l^t, \quad (1)$$

where $\delta(\cdot, \cdot)$ is the Kronecker delta, and y_l^t is the network output activation for label l at time t .

Cross-entropy trained LSTM acoustic models (AMs) are particularly appealing due to the simplicity and power of this loss function [30], a learning algorithm that lends itself well to efficient implementation for diverse model architectures and hardware [31–33]

2.3. GMM Alignments

Conventional phoneme-based systems use an existing speech recognizer to generate forced-alignments to get the boundaries of the phone segments, thus, assigning phoneme labels to the frames. Similarly, for CE-based grapheme AMs, we need frame-level graphemic alignments to provide the training labels. This approach of flat starting used in conventional phoneme-based models (e.g., [34]) can be applied to graphemes as well. Flat starting is particularly useful for training speech recognizers for new languages, which is often the use-case for a grapheme-based model.

Since GMMs are easy to train and have been studied extensively in the literature, we use them to generate initial alignments for the grapheme systems, using the training methodology similar to [35]. The speech signal is segmented evenly according to the target graphemic sequences, and the GMMs are trained to predict 3-state HMM context-independent graphemes using the Expectation Maximization (EM) algorithm. The input features are perceptual linear predictive features (PLPs) with

Table 1: Number of graphemes and phonemes per language

Language	# graphemes	# phonemes
Bengali	96	39
Tamil	90	35
Hindi	114	52
English	56	53

Table 2: Training and test data size

Language	# hour (train)	# hours (test)
Bengali	4.5K	4.1
Tamil	1.9K	6.4
Hindi	18K	7.2
English	18K	2.4

Table 3: WER : Phoneme and Grapheme models after CE and sMBR training

Language	CE-P	CE-G	sMBR-P	sMBR-G
Bengali	36.7	41.7	29.2	31.0(+1.8)
Tamil	41.5	43.2	30.3	31.9(+1.7)
Hindi	33.1	38.1	25.6	28.1(+2.5)
English	23.8	24.8	15.2	18.6(+3.4)

Table 4: WER: Acoustic models trained with GMM vs CE-LSTM alignments with Phoneme and Grapheme targets

Language	GMM-P	GMM-G	CE-P	CE-G
Bengali	36.7	41.7(+5.0)	32.9	35.7(+2.8)
Tamil	41.5	43.2(+1.7)	36.8	37.1(+0.3)
Hindi	33.1	38.1(+5.0)	30.7	34.2(+3.5)
English	23.8	24.8(+1.0)	22.6	23.1(+0.5)

deltas and delta-deltas [35], and the GMMs are trained with 14 mixtures per grapheme on less than 6% of the data for each language.

3. Experimental Setup and Results

For each of the four languages, Bengali, Tamil, Hindi and Indian English, we used the same amount of data for training the grapheme and phoneme models. Our training data consisted of anonymized, human-transcribed utterances representative of Google’s traffic. The amount of transcribed data per language is tabulated in Table 2. To achieve noise robustness the training data is augmented with varying degrees of noise and reverberation such that the overall SNR is between 0dB and 30dB, and the average SNR is 12dB [36]. The noise sources are from YouTube and daily life noisy environmental recordings.

The phoneme models were trained with the same recipe (Section 2) but using phoneme targets instead. All experiments used 80-dimensional log-mel features, computed with a 25ms window and shifted every 10ms. These features were stacked with 7 frames to the left and down-sampled to 30ms frame rate, following [37].

We used 5-layer×768 uni-directional LSTMs for cross-entropy training, which was followed by state-level minimum Bayes risk (sMBR) training [38], using the same model architecture. Standard FST-based beam-search decoders with 5-gram language models from the target languages were used for decoding.

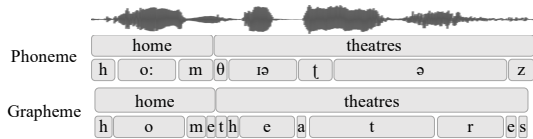


Figure 1: *Grapheme alignment example. From top to bottom: speech waveform, word alignment by the phoneme model, phoneme alignment, word alignment by the grapheme model, and grapheme alignment.*

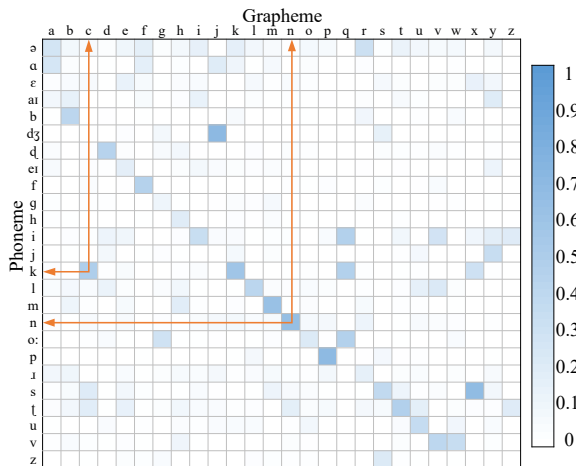


Figure 2: *Alignment confusion matrix for Indian English. Only a subset of phonemes/graphemes are kept for better visualization.*

Since Indian languages frequently contain Latin characters in the transcripts, all our models were evaluated after normalization for transliteration errors (*transliterated WER* [39]). Or in other words, if the model correctly decoded a word in Latin alphabet but the reference was in the native script (or vice versa), this was not considered an error.

Table 3 presents the WER of Phoneme and Grapheme models after CE and sMBR training, and we see an average improvement in performance of $\sim 27.5\%$ for all models after sequence training with sMBR criteria. Using the alignments generated by the respective CE models, we re-aligned and re-trained both phoneme and grapheme models. Both, phoneme and grapheme models showed a relative improvement between 5 to 15%; however, the gap between them also narrowed (Table 4). The suffixes **P** and **G** refer to **Phoneme** and **Grapheme** models in both the tables.

4. Alignments: Phoneme vs Grapheme

In order to study the alignments generated by the graphemic models, we compared these with phonemic alignments. An example of comparison is presented in Fig. 1. More generally, we generated the graphemic and phonemic alignments on the same set of utterances, which is presented in confusion matrices for English in Fig. 2, and for Bengali in Fig. 3. The matri-

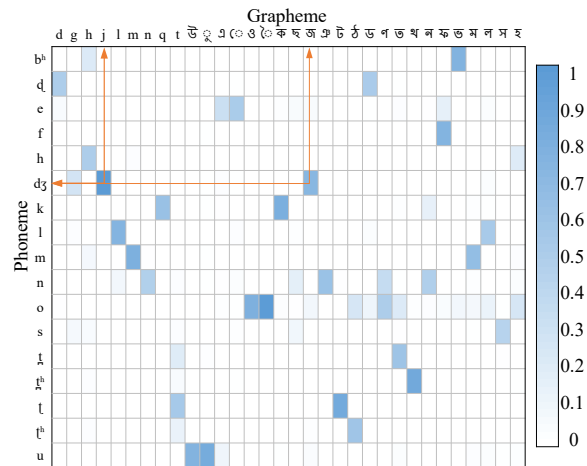


Figure 3: *Alignment confusion matrix for Bengali. Only a subset of phonemes/graphemes are kept for better visualization.*

ces are normalized by grapheme distribution (i.e., by columns). We can see that for Bengali, a language with strong phoneme-grapheme correspondence, the graphemes match their corresponding phonemes. For example, Bengali symbol “জ” is pronounced as “j” (as in “jug”), and is matched with the Bengali phoneme /dʒ/. For English, a language with irregular orthography, we observe that the grapheme alignments for consonants still mostly match, although the correspondence is weaker for vowels as can be seen in the confusion matrix in Fig. 2

5. Pronunciation in Grapheme Models

The languages studied in this paper come from three different regions of India and vary characteristically in pronunciation and orthography. Additionally, Indian English has its own distinctive accent which is influenced by the native language of the speaker. Naturally, for a grapheme recognizer that excludes the use of lexicon, we would like to understand how well the pronunciations are learnt. We carry out this exploration using the alignments generated by the grapheme models.

5.1. Accents

We investigate the grapheme-to-phoneme correspondence for two dialects (British and Indian English) using alignments from

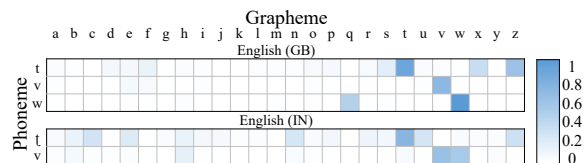


Figure 4: *Some examples of differences in the alignment confusion matrices between British (GB) and Indian (IN) English. Note that in our phoneme set, English (IN) does not have the phoneme “w.”*

Table 5: Agreement-score vs G-P WER gap

Language	Agreement-Score	(G-P) WER
Bengali	46.7%	1.8
Tamil	35.9%	1.7
Hindi	22.6%	2.5
English	9.4%	3.4

models trained on Indian and British English respectively in Fig. 4. Between the two dialects, we see clear differences in the grapheme-phoneme mapping, for instance, the grapheme “w” gets mapped to the phoneme “w” for British English, and to the phoneme “v” for Indian English. Likewise, the grapheme “r” is also mapped to different phonemes for the two dialects. As these sounds are characteristic to Indian English, we can confirm that accented pronunciations are learnt reliably by the grapheme recognizer simply from the training data.

5.2. Code-switching

Another important characteristic of Indian speech data is the use of words from multiple languages in the same utterance (code-switching). To better understand the pronunciation capability of grapheme models in this setup, we performed a few variants of the experiments reported above. When trained using graphemes and data from two languages (English and Bengali), we observed that the phonemes (e.g. /dʒ/) were mapped to the correct graphemes of both the languages (Fig. 3), demonstrating the ability of the recognizer to learn a sound that may be represented by graphemes of more than one language.

We also considered how the model behaves when constrained to the grapheme targets of a single language while being trained and tested with data from two languages. In an experiment where training and test data contained a mixture of Latin and Bangla script, and the model was provided with only the Bangla graphemes, we observed that the WER (after transliteration normalization) stayed the same (41.7, row 1 column 2 in Table 3), and the model learned to output phonetically equivalent English words with Bangla script (e.g. “সং” instead of “song”). These observations led us to believe that the grapheme models were inherently learning the script-agnostic phonetic pronunciations of the audio, in addition to the graphemic representations (spelling).

6. Error Analysis: Grapheme models

Qualitative analysis of the mistakes made by the grapheme models led us to believe that graphemes that did not have strong correspondence with any specific phoneme were confused more often. These mistakes surfaced as confusions in similar sounding words (homophones) or in groups of words. For instance, the spelling of the “u” sound between “stood” and “student”, were frequently interchanged. Similarly, the Bengali grapheme “ং” pronounced as “ng”, was replaced with “ন”, pronounced as “n” (and vice versa). To quantify this effect, we computed a metric, the “agreement score,” which we define as the fraction of graphemes aligning in at least half of their occurrences with a single phoneme.

$$agreement\ score = \frac{\sum_{g \in G} \delta_g}{\sum_{g \in G} 1} \quad (2)$$

where

$$\delta_g = \begin{cases} 1, & \text{if } \exists p \in P, f(g, p) \geq 0.5, \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

for the phoneme set P and grapheme set G .

Calculating the “agreement score” on 100K utterances for all four languages (Table 5), we observed that the higher the agreement-score, the lower the WER difference between the Phoneme and Grapheme models. This suggests that grapheme models might perform better on languages that have more regular phonemic orthography, (e.g. Spanish, Finnish, Polish, etc). Furthermore, we hypothesize that by improving the grapheme-to-phoneme correspondence in the training data, we can improve the performance of a grapheme model.

7. Summary

Building speech recognition system for a new language is always a challenge, especially in acquiring a pronunciation lexicon informed by linguistic knowledge. In this paper, we propose a simple methodology for training a grapheme-based recognizer from scratch with efficient training made possible by hardware acceleration. While graphemic LSTM-based recognizers have been previously explored, our proposed technique offers the additional advantage of generating good quality audio-to-grapheme alignments that are valuable for many speech applications such as captioning, keyword spotting and speech synthesis..

Furthermore, using four Indian languages, Bengali, Hindi, Tamil and Indian English with large-scale speech data, we show that our graphemic models can:

- Model the phonetic pronunciations independent of script and orthography.
- Capture pronunciations from different accents.
- Align a particular phonetic realization with multiple graphemes as seen in code-switched languages.
- Achieve performance comparable to lexicon-based models with the same number of parameters.
- Be combined with language models and FST decoders for a straightforward launch path for applied real-world usage.

We believe that our investigation will shed new light on how graphemes can be used for alternate lexicon-free speech recognition systems.

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