On The Inductive Bias of Words in Acoustics-to-Word Models

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Abstract

Acoustics-to-word models are end-to-end speech recognizers that use words as targets without relying on pronunciation dictionaries or graphemes. These models are notoriously difficult to train due to the lack of linguistic knowledge. It is also unclear how the amount of training data impacts the optimization and generalization of such models. In this work, we study the optimization and generalization of acoustics-to-word models under different amounts of training data. In addition, we study three types of inductive bias, leveraging a pronunciation dictionary, word boundary annotations, and constraints on word durations. We find that constraining word durations leads to the most improvement. Finally, we analyze the word embedding space learned by the model, and find that the space has a structure dominated by the pronunciation of words. This suggests that the contexts of words, instead of their phonetic structure, should be the future focus of inductive bias in acoustics-to-word models.

1 Introduction

Acoustics-to-word models are a special class of end-to-end models for automatic speech recognition (ASR) where the output targets are words [12, 2, 6, 5, 17, 19, 9]. In contrast to other end-to-end models where the output targets are phonemes or graphemes [7, 3], acoustics-to-word models directly predict words without relying on any intermediate lexical units. A parallel set of transcriptions (in words) and acoustic recordings is sufficient to train these models. This property offers a significant edge over conventional ASR systems, because acoustics-to-word models require minimal domain expertise to train and use, and might potentially be cheaper to build than conventional speech recognizers, depending on the cost of experts and obtaining the necessary resources.

When not given enough data, acoustics-to-word models are notoriously difficult to train [2]. The reason behind the difficulty is often attributed to the lack of inductive bias, e.g., linguistic knowledge about phonemes and the pronunciation of words. To improve the performance of acoustics-to-word models, much of the previous work has focused on injecting inductive bias to the models, such as initializing acoustics-to-word models with a pre-trained phone recognizer [2, 1, 19]. This approach has been shown to be critical in training acoustics-to-word models. However, it defeats the purpose of acoustics-to-word models by requiring a lexicon during training.

The central question is whether a lexicon is really necessary in training acoustics-to-word models. The result in [2] suggests that the optimization of acoustics-to-word models is inherently difficult, and they further argue that fitting the training set itself is difficult because there is not enough data. Additional inductive bias can provide a better initialization for optimizing the objective. However, it is unclear and rather counter-intuitive that fitting a small training set is more difficult than fitting a large one.

In this work, we first study the optimization of acoustics-to-word models. We show that, in contrast to previous studies, acoustics-to-word models are able fit a training set of various sizes without any inductive bias. We then study the sample complexity of acoustics-to-word models, and show that, instead of having
an all-or-none learning effect as seen in [2], the generalization error decreases as we increase the number of samples. In addition, we study the acoustics-to-word models under different inductive biases, including the pronunciation of words, word boundaries, and word durations. We also vary the amount of additional data needed for these inductive biases. These results characterize the optimization and generalization of acoustics-to-word models.

Given the ability to train an acoustics-to-word model end to end, it is natural to ask to what extent the common resources, such as the phoneme inventory, pronunciation dictionary, and language model, are learned by the model. We analyze the weights in the last layer for predicting words and find special structures in the word embedding space. These results show the limitation of acoustics-to-word models and shed light on future direction for improvement.

2 Acoustics-to-Word Models

The class of acoustics-to-word models can be either implemented with connectionist temporal classification (CTC) [4] or sequence-to-sequence models [9]. In this work, we focus on the case of CTC acoustics-to-word models.

Let $x = (x_1, \ldots, x_T)$ be an input sequence of $T$ acoustic feature vectors, or frames, where $x_t \in \mathbb{R}^d$ for $t = 1, \ldots, T$. Let $y = (y_1, \ldots, y_K)$ be an output sequence of $K$ labels, where $y_k \in L$ for $k = 1, \ldots, K$ and a vocabulary set $L$. For example, in our case, $x_t$ is a log-Mel feature vector, and $y_k$ is word. We use the $| \cdot |$ to denote the length of a sequence. For example, in this case, $|x| = T$ and $|y| = K$. The goal of the model is to map an input sequence to an output sequence.

In ASR, it is typical to have an output sequence shorter than the input sequence, i.e., $K < T$. In order to predict $K$ labels given $T$ frames, a CTC model predicts $T$ labels, allowing the prediction to have repeating labels and $\emptyset$’s, where $\emptyset$ is the blank symbol for predicting nothing. To get the final output sequence, there is a post-processing step $B$ that removes the repeating labels and the blank symbols, in that order. To train a CTC model, we maximize the conditional likelihood

$$p(y|x) = \sum_{z \in B^{-1}(y)} \prod_{t=1}^{T} p(z_t|x_t)$$

for a sample pair $(x, y)$, where $B^{-1}$ maps a label sequence of length $|y|$ to the set of all possible sequences of length $|x|$ by repeating labels and inserting $\emptyset$’s. In other words, the function $B^{-1}$ the pre-image of $B$, and note that $z_t \in L \cup \{\emptyset\}$ for $t = 1, \ldots, |x|$. The conditional likelihood and its gradient with respect to each individual $p(z_t|x_t)$ can be efficiently computed with dynamic programming [4].

The individual conditional probability $p(z_t|x_t)$ is typically modeled by a neural network. The input sequence $x_1, \ldots, x_T$ is first transformed into a sequence of hidden vectors $h_1, \ldots, h_T$, and $p(z_t|x_t) = \log \text{softmax}(W h_t)$ for $t = 1, \ldots, T$. Different studies have used different network architectures [7]. In this work, we use long short-term memory networks (LSTMs) to transform the input sequence.

3 Inductive Bias of Words

Given how little domain knowledge is used in acoustics-to-word models, much effort has been put into injecting inductive bias into acoustics-to-word models. In this section, we describe three approaches to achieve this.

3.1 Lexicon

A lexicon provides a mapping from a word to its canonical pronunciations. In conventional speech recognizers, hidden Markov models are constructed for each phoneme (under different contexts). Once the models are
trained, it is straightforward to generalize to unseen words by adding the pronunciations of those words to the lexicon.

In end-to-end speech recognizers, the need for a lexicon is sidestepped by using graphemes instead of phonemes as targets. Some end-to-end speech recognizers are able to generalize to unseen words this way, but it is still very difficult to add or remove a word from the vocabulary of an end-to-end speech recognizer. In terms of acoustics-to-word models, it is easy to remove a word from the vocabulary, but hard for the models to generalize to unseen words [5].

To make use of a lexicon, past studies train a phoneme-based CTC model on the phoneme sequences converted from word sequences in the training set [2, 1, 19]. Acoustics-to-word models are then initialized with the pre-trained phoneme-based CTC model with the hope that the acoustics-to-word models are able to utilize the phonetic knowledge encoded in the phoneme-based CTC model.

3.2 Word Boundary

Another type of inductive bias is word boundaries. Speech recognizers in general tend to perform worse on long utterances than short ones, and rely on insertion penalties to correct such bias. The training errors of long utterances are also typically higher than those of short ones. One hypothesis is that word boundaries are more difficult to pinpoint during training for long utterances than for short ones. In similar spirit, if we have access to word boundaries, we can train a frame classifier to encode the knowledge, and transfer it to acoustics-to-word models through initialization.

3.3 Word Duration

Another factor that makes pinpointing word boundaries difficult is the high variance of word durations. In the WSJ training set (si284), the average duration of a word (measured from the forced alignments) is 339.5 ms with a standard deviation of 198.0 ms, while the average duration of a phoneme is 81.6 ms with a standard deviation of 46.7 ms. These statistics show that it is more difficult to estimate the number of words in an utterance than the number of phonemes.

To introduce word duration bias in acoustics-to-word models, we down-sample the hidden vectors after each LSTM layer. Specifically, suppose \( h_1^n, \ldots, h_T^n \) is the output vectors produced by the \((n-1)\)-th LSTM layer after taking \( h_1^{n-1}, \ldots, h_T^{n-1} \) as input. Instead of the entire \( T \) vectors, we feed \( h_1^n, h_3^n, \ldots, h_{\lfloor T/2 \rfloor - 1}^n \) to the \( n \)-th LSTM layer. Every down-sampling reduces the frame rate by half. Down-sampling has been introduced in the past for speeding up inference [18, 8, 15], but it can also act as imposing a constraint on the minimum word duration [14].

4 Experiments

We choose the Wall Street Journal data set (WSJ0 and WSJ1) for our experiments for the wide variety of words and rich word usage in the data set. It consists of 80 hours of read speech and 13,635 unique words in the training set (si284). We follow the standard protocol using 90% of the si284 for training, 10% of si284 for development, and dev93 and eval92 for testing. We obtain forced alignments of words and phonemes with a speaker-adaptive Kaldi system, following the standard recipe [10]. We extract 80-dimensional log-Mel features, and use them as input without concatenating i-vectors. We use a 4-layer unidirectional LSTM with 500 units per layer. The softmax targets at each time step are the 13,635 words plus the blank symbol (\( \emptyset \)).

The LSTMs are trained by minimizing the CTC loss with vanilla stochastic gradient descent (SGD) for 20 epochs, a step size of 0.05, and gradient clipping of norm 5. The mini-batch size is one utterance. The best model within the 20 epochs is selected and trained for another 20 epochs with learning rate 0.0375 decayed by 0.75 after each epoch. The best model out of the 40 epochs is used for evaluation. No additional regularization is used.

To see how the amount of data impacts optimization and generalization, we train the LSTMs on different amounts of training data, one-half of si84 (around 5 hours), si84 (around 10 hours), one-half of si284 (around 10 hours), and si284 (around 20 hours).
Table 1: WERs (%) of acoustics-to-word models trained on different sizes of the training set. The last column is the training perplexity of the last epoch.

| train     | dev | dev93 | eval92 | si284 |
|-----------|-----|-------|--------|-------|
| si84-half | 63.0| 64.8  | 58.3   | 1.27  |
| si84      | 51.9| 55.1  | 45.1   | 0.54  |
| si284-half| 32.9| 36.2  | 33.5   | 0.40  |
| si284     | 21.4| 29.4  | 26.3   | 0.34  |

Table 2: PERs (%) of phoneme-based CTC models trained on different sizes of the training set.

| train     | dev | dev93 | eval92 |
|-----------|-----|-------|--------|
| si84-half | 38.0| 40.0  | 26.1   |
| si84      | 27.7| 29.1  | 16.1   |
| si284-half| 16.1| 15.0  | 12.4   |
| si284     | 12.3| 11.9  | 9.4    |

(around 35 hours) and the entire si284 (around 70 hours). Results are shown in Table 1. We measure the training perplexity of the last epoch, i.e., the sum of cross entropy at each frame divided by the number labels (as opposed to the number of frames). Except for the one with half of si84, the other three models are able to fit the training set without trouble. Note that the models receive different numbers of gradient updates, so it is not surprising that lower training error is observed when using more data. The generalization error is better when using more data as expected.

To introduce the inductive bias given by the lexicon, we train a 3-layer LSTM phoneme-based CTC model using the same training procedure. The quality of the phoneme recognizer is shown in Table 2, and the performance is on par with the state of the art of a similar architecture [7]. Similarly, to introduce the inductive bias of word boundaries, we train a 4-layer LSTM word frame classifier with a lookahead of one frame and online decoding [13]. The quality of the word frame classifier is shown in Table 3. This architecture with additional lookahead is able to achieve state-of-the-art frame error rates [13]. However, to limit the confounding factors, we fix the lookahead to one.

To see the impact of the amount of training data, we initialize the acoustics-to-word models with phoneme-based CTC models and word frame classifiers trained on different amounts of training data. The bottom three layers of LSTMs are initialized with the various pre-trained models. In other words, the last layer of the frame classifier is discarded. The last layer and the softmax layer of the initialized acoustics-to-word model is randomly initialized the same way as the baseline models were. This number of layers for initialization is motivated by recent success in multitask CTC [16, 11]. As a comparison, we also have a set of acoustics-to-word models initialized with the bottom three layers of the trained acoustics-to-word models in Table 1. Results are shown in Table 4. Not only do we see no improvement in initializing with phoneme-based CTC models and frame classifiers, it actually hurts performance in many cases. Small improvements from initializing with acoustics-to-word models themselves has been observed, with the best model achieving 27.5% WER on dev93 and 24.4% on eval92.

Finally, we experiment with the amount of down-sampling in LSTM layers. We have four LSTMs with increasing amount of down-sampling after the input. Results are shown in Table 5. We see significant improvement, with the best having a down-sampling factor of four. This is consistent with the commonly used frame rate [18, 8, 15, 14].
Table 3: FERs (%) of word frame classifiers trained on different sizes of the training set.

| train     | dev | dev93 | eval92 |
|-----------|-----|-------|--------|
| si84-half| 67.4| 62.4  | 61.7   |
| si84     | 56.0| 55.3  | 53.2   |
| si284-half| 40.6| 46.3  | 47.2   |
| si284    | 28.3| 44.3  | 45.7   |

Table 4: WERs (%) on the development set for acoustics-to-word models initialized from different models. The first column indicates the amount of data on which the initial models are trained.

| phoneme | CTC | word frame | word CTC |
|---------|-----|------------|----------|
| si84-half| 27.4| 25.9       | 22.3     |
| si84    | 28.9| 24.8       | 21.9     |
| si284-half| 25.0| 31.1       | 20.6     |
| si284   | 21.1| 22.0       | 19.4     |

Table 5: WERs (%) of acoustics-to-word models for different amount of down-sampling in the LSTM layers.

| down-sampling | dev | dev93 | eval92 |
|---------------|-----|-------|--------|
| 2^0           | 21.4| 29.4  | 26.3   |
| 2^1           | 21.8|       |        |
| 2^2           | 17.7| 26.8  | 24.6   |
| 2^3           | 18.6|       |        |
| 2^4           | 18.8|       |        |
Figure 1: The histogram of the amount of overlap (normalized by the number of phonemes in the shorter word) in canonical pronunciations of a word to its close neighbors (the first to the third nearest neighbor) and far neighbors (the 48th to the 50th nearest neighbor).

Figure 2: The histogram of distances from a word to its top 25 nearest neighbors. The average distance of \(<\text{blk}>\) (i.e., \(\emptyset\)) to its nearest neighbors is shown in dashed red.

5 Analysis

The gap between the results in Table 1 and the state-of-the-art end-to-end system [20], i.e., 14.1% absolute on eval92, is large, and it shows that a vanilla acoustics-to-word model does not perform well out of the box. A phoneme-based CTC model with a lexicon and without a language model can achieve 26.9% WER on eval92 [7]. Based on these results and the best down-sampling factor, it is likely that the model only learns to map acoustic features to words without utilizing the dependencies between words much.

To confirm this hypothesis and to understand how words are arranged in the embedding space, we analyze the weights of the softmax layer. Given a word, we take its corresponding weight vector in the softmax layer and compute its nearest neighbors. We first notice that similar pronouncing words tend to be nearest neighbors of each other. To see this, we define the overlap (in canonical pronunciation) as the number of phoneme tokens appeared in both words divided by the length of the shorter word. We compare the overlaps of words from two groups, the word to its close neighbors (the first to the third neighbor) and the word to its far neighbors (the 48th to the 50th neighbor). As shown in Fig. 1, the close neighbors have more similar pronunciations than the far neighbors. This confirms the hypothesis that the model relies more on the acoustics rather than the language to predict words.

We then notice that the blank symbol is significantly further away (in L2 distance) from other words, and this can be seen from the histogram of distances in Fig. 2. We refer to the distance between a word and its first nearest neighbor as the margin. In other words, the margin of the blank symbol is significantly larger than that of other words. We then notice that the margin is related to the occurrence of words in the training set, as is shown in Fig. 3. This might be the consequence of conditional independence assumed in the CTC loss. If this is indeed the case, improved performance can only be achieved through a different objective or an inductive bias on word dependency.
Figure 3: The number of times a word appears in the training set against the distance to its first nearest neighbor. The point in the upper right corner is SIL (the silence).

6 Conclusion

In this work, we study the optimization and generalization of acoustics-to-word models. We find that the models are able to fit data sets of various sizes without trouble. The generalization error decreases as expected, as we increase the amount of training data. In contrast to other studies, we find no improvement in initializing the models with a pre-trained phoneme-based CTC model or a word frame classifier. Down-sampling the hidden vectors after the LSTM layer provides significant improvement. To understand what hinders the performance, we analyze the word embeddings learned by the model. The model discovers similar sounding words and places them in the corresponding neighborhood. However, the model might not be utilizing the label dependency much during decoding. This suggests that label dependency should be the future focus of inductive bias in acoustics-to-word models.

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