ABSTRACT

In automatic speech recognition (ASR) what a user says depends on the particular context she is in. Typically, this context is represented as a set of word n-grams. In this work, we present a novel, all-neural, end-to-end (E2E) ASR system that utilizes such context. Our approach, which we refer to as Contextual Listen, Attend and Spell (CLAS) jointly-optimizes the ASR components along with embeddings of the context n-grams. During inference, the CLAS system can be presented with context phrases which might contain out-of-vocabulary (OOV) terms not seen during training. We compare our proposed system to a more traditional contextualization approach, which performs shallow-fusion between independently trained LAS and contextual n-gram models during beam search. Across a number of tasks, we find that the proposed CLAS system outperforms the baseline method by as much as 68% relative WER, indicating the advantage of joint optimization over individually trained components.

Index Terms: speech recognition, sequence-to-sequence models, listen attend and spell, LAS, attention, embedded speech recognition.

1. INTRODUCTION

As speech technologies become increasingly pervasive, speech is emerging as one of the main input modalities on mobile devices and in intelligent personal assistants [1]. In such applications, speech recognition performance can be improved significantly by incorporating information about the speaker’s context into the recognition process [2]. Examples of such context include the dialog state (e.g., we might want “stop” or “cancel” to be more likely when an alarm is ringing), the speaker’s location (which might make nearby restaurants or locations more likely) [3], as well as personalized information about the user such as her contacts or song playlists [4].

There has been growing interest recently in building sequence-to-sequence models for automatic speech recognition (ASR), which directly output words, word-pieces [5], or graphemes given an input speech utterance. Such models implicitly subsume the components of a traditional ASR system - the acoustic model (AM), the pronunciation model (PM), and the language model (LM) - into a single neural network which is jointly trained to optimize log-likelihood or task-specific objectives such as the expected word error rate (WER) [6]. Representative examples of this approach include connectionist temporal classification (CTC) [7] with word output targets [8], the recurrent neural network transducer (RNN-T) [9, 10], and the “Listen, Attend, and Spell” (LAS) encoder-decoder architecture [11, 12]. In recent work, we have shown that such approaches can outperform a state-of-the-art conventional ASR system when trained on 12,500 hours of transcribed speech utterances [13].

In the present work, we consider techniques for incorporating contextual information dynamically into the recognition process. In traditional ASR systems, one of the dominant paradigms for incorporating such information involves the use of an independently-trained on-the-fly (OTF) rescoring framework which dynamically adjusts the LM weights of a small number of n-grams relevant to the particular recognition context [2]. Extending such techniques to sequence-to-sequence models is important for improving system performance, and is an active area of research. In this context, previous works have examined the inclusion of a separate LM component into the recognition process through either shallow fusion [14], or cold fusion [15] which can bias the recognition process towards a task-specific LM. A shallow fusion approach was also directly used to contextualize LAS in [16] where output probabilities were modified using a special weighted finite state transducer (WFST) constructed from the speaker’s context, and was shown to be effective in improving performance.

The use of an external independently-trained LM for OTF rescoring, as in previous approaches, goes against the benefits derived from the joint optimization of the components of a sequence-to-sequence model. Therefore, in this work, we propose Contextual-LAS (CLAS), a novel, all-neural mechanism which can leverage contextual information – provided as a list of contextual phrases – to improve recognition performance. Our technique consists of first embedding each phrase, represented as a sequence of graphemes, into a fixed-dimensional representation, and then employing an attention mechanism [17] to summarize the available context at each step of the model’s output predictions. Our approach can be considered to be a generalization of the technique proposed in [18] in the context of streaming keyword spotting, by allowing for a variable number of contextual phrases during inference. The proposed method does not require that the
particular context information be available at training time, and crucially, unlike previous works \cite{16,2}, the method does not require careful tuning of rescoring weights, while still being able to incorporate out-of-vocabulary (OOV) terms. In experimental evaluations, we find that CLAS -- which trains the contextualization components jointly with the rest of the model -- significantly outperforms online rescoring techniques when handling hundreds of context phrases, and is comparable to these techniques when handling thousands of phrases.

The organization of the rest of this paper is as follows. In Section 2.1 we describe the standard LAS model, and the standard contextualization approach in Section 2.2. We present the proposed modifications to the LAS model in order to obtain the CLAS model in Section 3. We describe our experimental setup and discuss results in Sections 4 and 5 respectively, before concluding in Section 6.

2. BACKGROUND

2.1. The LAS model

We now briefly describe the LAS model. For more details see \cite{11,13}. The LAS model outputs a probability distribution over sequences of output labels, $y$, (graphemes, in this work) conditioned on a sequence of input audio frames, $x$ (log-mel features, in this work): $P(y|x)$.

\begin{equation}
 P(y|x) = \frac{1}{Z(x)} \exp \left( \sum_{t=1}^{T} \log P(y_t|x, y_{<t}) \right),
\end{equation}

where $Z(x)$ is a normalizer, and $P(y_t|x, y_{<t})$ represents the conditional probability of the output at time step $t$. The conditional probability is given as:

\begin{equation}
 P(y_t|x, y_{<t}) = \frac{1}{Z_t(y_{<t})} \exp \left( \sum_{t=1}^{T} \log P(y_t|x, y_{<t}) \right),
\end{equation}

where $Z_t(y_{<t})$ is a normalizer for the output at time step $t$.

The conditional dependence on the encoder state vectors, $h^x_t$, is modeled using a context vector $c_t = c^x_t$, which is computed using Multi-Head-attention \cite{21,13} as a function of the current decoder hidden state, $d_t$, and the full encoder state sequence, $h^x$.

\begin{equation}
 c_t = \text{Multi-Head-attention}(d_t, h^x_{<t})
\end{equation}

The hidden state of the decoder, $d_t$, which captures the previous character context $y_{<t}$, is given by:

\begin{equation}
 d_t = \text{RNN}(\tilde{y}_{t-1}, d_{t-1}, c_{t-1})
\end{equation}

where $d_{t-1}$ is the previous hidden state of the decoder, and $\tilde{y}_{t-1}$ is an embedding vector for $y_{t-1}$. The posterior distribution of the output at time step $t$ is given by:

\begin{equation}
 P(y_t|h^x, y_{<t}) = \text{softmax}(W_y[c_t; d_t] + b_y),
\end{equation}

where $W_y$ and $b_y$ are again learnable parameters, and $[c_t; d_t]$ represents the concatenation of the two vectors. The model is trained to minimize the discriminative loss:

\begin{equation}
 L_{\text{LAS}} = -\log P(y|x)
\end{equation}

2.2. On-the-fly Rescoring

On-the-fly rescoring (similar to \cite{22}) serves as one of our baseline approaches. Specifically, we assume that a set of word-level biasing phrases are known ahead of time, and compile them into a weighted finite state transducer (WFST) \cite{23}. This word-level WFST, $G$, is then left-composed with a “speller” FST, $S$, which transduces a sequence of graphemes/word-pieces into the corresponding word. Following the procedure used by \cite{12} for a general language model, we obtain the contextual LM, $C = \min(\det(S \circ G))$. The scores from the contextualized LM, $P_C(y)$, can then be incorporated into the decoding criterion, by augmenting the standard log-likelihood term with a scaled contribution from the contextualized LM:

\begin{equation}
 y^* = \arg \max_y \log P(y|x) + \lambda \log P_C(y)
\end{equation}

where, $\lambda$ is a tunable hyperparameter controlling how much the contextual LM influences the overall model score during beam search.

Note that in \cite{22}, no weight pushing was applied. Consequently, the overall score in Equation (5) is only applied at word boundaries. This is shown in Figure (3b). Thus, this technique cannot improve performance if the relevant word does not first appear on the beam. Furthermore, we observe that while this approach works reasonably well when the number of contextual phrases is small (e.g., yes, no, cancel) \cite{22}, it does...
not work well when the list of contextual phrases contains many proper nouns (e.g., song names or contacts). If weight pushing is used, similarly to [12], the score will only be applied to the beginning subword unit of each word as shown in Figure 2, which might cause over-biasing problems as we might artificially boost words early on. Therefore, we explore pushing weights to each subword unit of the word, illustrated in Figure 4. To avoid artificially giving weight to prefixes which are boosted early on but do not match the entire phrase, we also include a subtractive cost, as indicated by the negative weights in the figure. We compare all three approaches in the results section.

![Fig. 2. Different techniques for applying subword-unit scores. Note the costs (i.e., −1) are model parameters, and are tuned during inference.](image)

### 3. CONTEXTUAL LAS (CLAS)

We will now introduce the Contextualized LAS (CLAS) model which uses additional context through a list of provided bias phrases, \( z \), thus effectively modeling \( P(y|x, z) \). The individual elements in \( z \) represent phrases such as personalized contact names, song lists, etc., which are relevant to the particular recognition context.

#### 3.1. Architecture

We now describe the modification made to the standard LAS model (Figure 1a) in order to obtain the CLAS model (Figure 1b). The main difference between the two models is the presence of an additional bias-encoder with a corresponding attention mechanism. These components are described below.

In order to contextualize the model, we assume that the model has access to a list of additional sequences of bias-phrases, denoted as \( z = za, ..., zN \). The purpose of the bias phrases is to bias the model towards outputting particular phrases. However, not all bias phrases are necessarily relevant given the current utterance, and it is up to the model to determine which phrases (if any) might be relevant and to use these to modify the target distribution \( P(y|h, z) \).

We augment LAS with a bias-encoder which embeds the bias-phrases into a set of vectors \( h^z = \{h^z_0, h^z_1, ..., h^z_N\} \) (we use superscript \( z \) to distinguish bias-attention variables from audio-related variables). \( h^z_i \) is an embedding of \( z_i \) if \( i > 0 \). Since the bias phrases may not be relevant for the current utterance, we include an additional learnable vector, \( h^z_0 = h^z_{\text{no-bias}} \), that corresponds to the the no-bias option, that is not using any of the bias phrases to produce the output. This option enables the model to backoff to a “bias-less” decoding strategy when none of the bias-phrases matches the audio, and allows the model to ignore the bias phrases altogether. The bias-encoder is a multilayer long short-term memory network (LSTM) [19]; the embedding, \( h^z_i \), is obtained by feeding the bias-encoder with the sequence of embeddings of subwords in \( z_i \) (i.e., the same grapheme or word-piece units used by the decoder) and using the last state of the LSTM as the embedding of the entire phrase [24].

Attention is then computed over \( h^z \), using a separate attention mechanism from the one used for the audio-encoder. A secondary context vector \( c^z_t \) is computed using the decoder state \( d_t \).

![Fig. 3. Example of bias-attention-probabilities, \( \alpha^z_t \), for an utterance with reference text "talk to what fruit are you". The utterance was decoded with 3,250 bias phrases, we show here the most active ones. Brighter colors denote values closer to 1, while darker colors indicate values closer to 0. The x-axis is decoding step \( t \), and the strings on the left are the most active bias phrases. Here we use $\$ do denote the </bias> token (see section 3.2).](image)

The LAS context vector, which feeds into the decoder, \( c_t \) is then modified by setting \( c_t = [c^z_t; c^z_t] \), the concatenation of context vectors obtained with respect to \( x \) and \( z \). The other components of the CLAS model (i.e., decoder and audio-encoder) are identical to the corresponding components in the standard LAS model.

It is worth noting that CLAS explicitly models the probability of seeing a particular bias phrase given the audio and previous outputs:

\[
\alpha^z_t = P(z_t|d_t) = P(z_t|x; y_{<t})
\]

We refer to \( \alpha^z_t \) as bias-attention-probability and an example of it is presented in Figure 5.
3.2. Training

The CLAS model is trained to minimize the loss:

\[ L_{\text{CLAS}} = - \log P(y|x, z) \]  

where, the bias list, \( z \), is randomly generated at run time during training for each training batch. This is done to allow flexibility in inference, as the model does not make any assumption about what bias phrases will be used during inference. The training bias-phrase list is randomly created from the reference transcripts associated with the utterances in the training batch. The bias list creation process takes a list of reference transcripts, \( r_1, \ldots, r_{N_{\text{bias}}} \), corresponding to the audio in a training batch, and randomly selects a list, \( z \), of \( n \)-gram phrases that appear as substrings in some of the reference transcripts.

To exercise the ‘no-bias’ option, which means that \( z \) does not match some of the utterances in the batch, we exclude each reference with probability \( P_{\text{keep}} \) from the creation process. When a reference is discarded we still keep the utterance in the batch, but do not extract any bias phrases from its transcript. If we set \( P_{\text{keep}} = 0 \) no bias phrases will be presented to the training batch, and \( P_{\text{keep}} = 1 \) means that each utterance in the batch will have at least one matching bias phrase.

Next, \( k \) word \( n \)-grams are randomly selected from each kept reference, where \( k \) is picked uniformly from \([1, N_{\text{phrases}}]\) and \( n \) is picked uniformly from \([1, \text{N}_{\text{order}}]\).

\( P_{\text{keep}}, N_{\text{phrases}} \) and \( \text{N}_{\text{order}} \) are hyperparameters of the training process. For example, if we set \( P_{\text{keep}} = 1.0 \), \( N_{\text{phrases}} = 1 \), \( \text{N}_{\text{order}} = 1 \), one unigram will be selected from each reference transcript. Other choices will be discussed in the experimental section.

Once a set \( z \) is (randomly) selected, we proceed by computing the intersection of \( z \) with each reference transcript \( r \). Every time a match is found a special \(<\text{bias}>\) symbol is inserted after the match. For example, if the reference transcript is \( \text{play a song} \), and the matching bias phrase is \( \text{play} \), the target sequence will be modified to \( \text{play}<\text{bias}>\text{a song} \). The purpose of \(<\text{bias}>\) is to introduce a training error which can be corrected only by considering the correct bias phrase [13]. In other words, to be able to predict \(<\text{bias}>\) the model has to attend to the correct bias phrase, thus ensuring that the bias-encoder will receive updates during training.

3.3. Inference

During inference, the user provides the system with a sequence of audio feature vectors, \( x \), and a set of context sequences, \( z \), possibly never seen in training. Using the bias-encoder, \( z \) is embedded into \( h^z \). This embedding can take place before audio streaming begins. The audio frames, \( x \), are then fed into the audio encoder, and the decoder is run as in standard LAS to produce N-best hypotheses using beam-search decoding [24].

3.4. Bias-Conditioning

When thousands of phrases are presented to CLAS, retrieving a meaningful bias context vector becomes challenging, since it is the weighted sum of many different bias-embeddings, and might be far from any context vector seen in training. Bias-Conditioning attempts to alleviate this problem. Here we assume that during inference the model is provided with both a list of bias phrases, \( z = z_1, \ldots, z_N \), as well as a list of bias prefixes, \( p = p_1, \ldots, p_N \). With this technique a bias phrase \( z_i \) is “enabled” at step \( t \) only when \( p_i \) was detected on the partial hypothesis \( y_{<t} \) (the partially decoded hypothesis on the beam). In practice, we do this by updating the bias-attention-probabilities in Equation 7 by setting:

\[ m_{it} = \begin{cases} 0 & \text{if } p_i \subseteq y_{<t} \\ \infty & \text{otherwise} \end{cases} \]  

\[ \alpha_t^i = \text{softmax}(u_t^i - m_t) \]  

where, \( \subseteq \) is string inclusion. The list of bias prefixes can be constructed arbitrarily. For example, we might want to condition the bias-phrase the cat sat on the bias-prefix the cat. In this case we will compute an embedding for the cat sat but “enable” it only once the cat is detected in \( y_{<t} \).

A good choice of prefixes will minimize the number of phrases sharing the same prefix, so the bias-attention is not “overloaded”, while at the same time, not splitting each phrase into too many segments, to allow distinctive bias embeddings. This may be achieved by an algorithm which starts from empty prefixes \( (p_i = \varepsilon) \) and iteratively extends each prefix by one word (from \( z_i \)) as long as the same prefix is not shared by too many phrases. In the Section 5.3.3 we discuss a rule-based prefix construction, and leave full algorithmic treatment as future work.

4. EXPERIMENTS

4.1. Experimental Setup

Our training setup is similar to [13], though our experiments focus on graphemes and our model architecture is smaller. Our experiments are conducted on a ~25,000 hour training set consisting of 33 million English utterances. The training utterances are anonymized and hand-transcribed, and are representative of Google’s voice search traffic. This data set is augmented by artificially corrupting clean utterances using a room simulator, adding varying degrees of noise and reverberation such that the overall SNR is between 0dB and 30dB, with an average SNR of 12dB [25]. The noise sources are from YouTube and daily life noisy environmental recordings.

The models evaluated in this section are trained on 8 x 8 Tensor Processing Units (TPU) slices with global batch size of 4,096. Each training core operates on a shard-size of 32
utterances in each training step. From this shard, bias phrases are randomized and thus each shard sees a maximum of 32 bias phrases during training.

We use 80-dimensional log-mel acoustic features computed every 10ms over a 25ms window. Following [13] we stack 3 consecutive frames and stride the stacked frames by a factor of 3. This downsampling enables us to use a simpler encoder architecture than [11].

The encoder’s architecture consists of 10 unidirectional LSTM layers, each with 256 nodes. The encoder-attention is computed over 512 dimensions, using 4 attention heads. The bias-encoder consists of a single LSTM layer with 512 nodes and the bias-attention is computed over 512 dimensions. Finally, the decoder consists of 4 LSTM layers with 256 nodes. In total, the model has about 58 million trainable parameters. Our model is implemented using TensorFlow [26].

In all our experiments we set $P_{\text{keep}} = 0.5$ to promote robustness to the ‘no-bias’ case. We set $N_{\text{phrases}} = 1$ and $N_{\text{order}} = 4$. This leads to a bias list with expected size of 17 (half of the shard size, plus one for ‘no-bias’).

### 4.2. Test sets

We test our model on a number of test sets, which we describe below. A summary of the biasing setup of each of the test sets is given in Table 1.

| Test Set   | Number of utterances | Average bias list size | Bias OOV rate |
|------------|----------------------|------------------------|---------------|
| Voice Search | 14k                  | -                      | -             |
| Dictation  | 15k                  | 303                    | 3.5%          |
| Songs      | 15k                  | 75                     | 5.2%          |
| Contacts   | 15k                  | 3,255                  | 5.6%          |
| Talk-To    | 4k                   |                        |               |

Table 1. Details of evaluated test sets. The ‘bias OOV rate’ measures the fraction of unique words appearing in the bias lists which are not seen in the training data.

The Voice Search test set contains voice search queries which are about 3 seconds long. The Dictation test set contains longer utterances, such as dictations of text messages. Both Voice Search and Dictation are in matched conditions to portions of the training data, and are not used to test biasing but rather the performance of the model in a bias-free setting.

Each of the remaining test sets: Songs, Contacts, and Talk-To, contain utterances with a distinct list of contextual phrases which vary from four phrases up to more than three thousand, and are not necessarily identical across utterances.

The Songs test set contains requests to play music (e.g. play rihanna music) with a bias set that contains popular american song and artist names. The Contacts test set contains call requests (e.g. call demetri mobile) with a bias set that contains an arbitrary list of contact names.

The Talk-To test set contains requests to talk with one of many chatbots (e.g. talk to trivia game). We note that the list of available chatbots is rather large compared to previous sets. See Table 1 for more details.

### 5. RESULTS

In this section, we present the performance of CLAS across a variety of test sets.

#### 5.1. CLAS without bias phrases

First, to check if our biasing components hurt decoding in cases where no bias phrases are present, we compare our model to a similar ‘vanilla’ LAS system in table 2. We note that the CLAS model is trained with random bias phrases, but evaluated with an empty list of phrases during inference (i.e., only ‘no-bias’ is presented at inference time), we denote this model by CLAS-NB. Somewhat surprisingly, we observe that CLAS-NB does better than LAS, and conclude that CLAS can be used even without any biasing phrases. Therefore, in the experiments that follow, to get accurate comparison, instead of comparing to LAS directly we use CLAS-NB as proxy for a LAS baseline.

| Test Set   | LAS WER (%) | CLAS-NB WER (%) |
|------------|-------------|-----------------|
| Voice Search | 6.9         | 6.4             |
| Dictation  | 5.5         | 4.5             |

Table 2. LAS vs CLAS where no bias phrases are provided.

#### 5.2. On-the-fly (OTF) Rescoring with LAS Baseline

Table 3 compares different OTF rescoring variants, which differ in how weights are assigned to subword units as outlined in Section 2.2. We only report numbers for the Songs test set; similar trends were observed on the other test sets, which are omitted in the interest of brevity. The table indicates that if we bias at the end of the word, as done in [22], we get very little improvement over the no-bias baseline. While a small improvement comes from biasing at the beginning of each word [12], the best system biases each subword unit, which helps to keep the word on the beam. All subsequent experiments with OTF rescoring will thus bias each subword unit.

| Method                                      | Songs |
|---------------------------------------------|-------|
| No Bias (LAS)                               | 20.9  |
| LAS + End of Word Bias [13]                  | 19    |
| LAS + Beginning of Word Bias                | 16.5  |
| LAS + Every Subword Unit w/ Subtractive Cost Bias | 9.4   |

Table 3. LAS with different ways of contextual biasing.
5.3. CLAS with bias phrases

5.3.1. Comparison of Biasing Approaches

| Test Set | CLAS | CLAS + OTF | CLAS + Cond | CLAS + Cond + OTF |
|----------|------|------------|-------------|-------------------|
| Songs    | 18.7 | 9.4        | 6.9         | -                 |
| Contacts | 28   | 17.7       | 7.9         | -                 |
| Talk-To  | 10.8 | 5.2        | 14          | -                 |

Table 4. WER for CLAS and baseline approaches

We compare CLAS to two baseline approaches in Table 4: (1) A LAS baseline, using CLAS-NB as explained in Section 5.1, (2) LAS + OTF rescoring as described in Section 2.2, with λ estimated on the same test sets. We find that on sets that have hundreds of biasing phrases with high rate of OOVs (Songs, Contacts), CLAS performs significantly better compared to traditional approaches without requiring any additional hyperparameter tuning. However, CLAS degrades on the Talk-To set which has thousands of phrases. This scalability issue will be addressed with bias-conditioning (see Section 5.3.3).

5.3.2. CLAS with varying number of bias phrases

To better understand the CLAS failure with Talk-To we evaluate CLAS while restricting to phrases that appear in the reference transcript plus \( N \) distractors (phrases which are not present in the transcript) chosen randomly from the complete bias list. The results are presented in Figure 4. We observe gradual degradation in WER as a function of number of distractors.

![Fig. 4. WER for the Talk-To set with a CLAS model (without rescoring or conditioning).](image)

We hypothesise that the reason for this behavior is that with a large number of bias phrases, correlations start to appear between their embeddings. For example, the embeddings of talking pal and talkative ai have a correlation (normalized inner product) of 0.6, while the average correlation is 0.2.

5.3.3. Overcoming the scaling problem: CLAS with Bias-conditioning (Cond) and OTF rescoring

Next, we try to combine CLAS with bias-conditioning (Section 3.4). Since Talk-to has the largest number of biasing phrases, we test scalability of CLAS by applying bias-conditioning to this set only, with prefixes constructed in a rule-based manner: First we create a prefix from talk to + the next word, (e.g. the phrase talk to pharmacy flashcards, would be split into a prefix \( p_i = \) talk to pharmacy and a suffix \( z_i = \) flashcards). In addition we found it useful to condition the first word after talk to on its first letter (e.g. pharmacy will be conditioned on talk to p). This construction restricts the number of phrases sharing the same prefix to 225 (vs. 3255) while increasing the overall number of bias phrase segments by only 10%.

In Table 5 with show our bias-conditioning and OTF-rescoring (Section 2.2) CLAS results. CLAS benefits from either approach, as well as from their combination. Indeed, conditioning allows us to scale to a large number of phrases without any degradation.

| Test Set | CLAS + OTF | CLAS + Cond | CLAS + Cond + OTF |
|----------|------------|-------------|-------------------|
| Songs    | 6.9        | -           | -                 |
| Contacts | 7.9        | 7.5         | -                 |
| Talk-To  | 14         | 9.0         | 7.4               |
|          |            |             | 5.6               |

Table 5. WER for biasing test set. The results show the benefit for CLAS from both Conditioning and OTF rescoring.

6. CONCLUSIONS

In this work we presented CLAS, a novel, all-neural, end-to-end contextualized ASR model, which incorporates contextual information by embedding full context phrases. In experimental evaluations, we demonstrated how the proposed model outperforms standard shallow-fusion biasing techniques on several test sets. We investigated CLAS’s ability to handle a large set of context phrases, and suggested a conditioning method to further improve its quality. Our future work includes scaling CLAS to tens of thousands of bias phrases.

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