Contextual Density Ratio for Language Model Biasing of Sequence to Sequence ASR Systems

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Abstract

End-2-end (E2E) models have become increasingly popular in some ASR tasks because of their performance and advantages. These E2E models directly approximate the posterior distribution of tokens given the acoustic inputs. Consequently, the E2E systems implicitly define a language model (LM) over the output tokens, which makes the exploitation of independently trained language models less straightforward than in conventional ASR systems. This makes it difficult to dynamically adapt E2E ASR system to contextual profiles for better recognizing special words such as named entities. In this work, we propose a contextual density ratio approach for both training a contextual aware E2E model and adapting the language model to named entities. We apply the aforementioned technique to an E2E ASR system, which transcribes doctor and patient conversations, for better adapting the E2E system to the names in the conversations. Our proposed technique achieves a relative improvement of up to 46.5% on the names over an E2E baseline without degrading the overall recognition accuracy of the whole test set. Moreover, it also surpasses a contextual shallow fusion baseline by 22.1 % relative.

Index Terms: speech recognition, end-to-end, sequence-to-sequence, language model, shallow fusion, density ratio

1. Introduction

In recent years, End-to-end (E2E) systems have been greatly adopted for ASR because of their performance and simplicity. In conventional ASR systems, several components, such as the pronunciation lexicon, the language models, and the acoustic model, are optimized independently. In contrast, E2E systems integrate all components of conventional ASR systems in a single neural network by directly approximating the posterior probability given the acoustic features.

Despite the direct posterior approximation simplifying many aspects such as training, decoding and deployment, these advantages do not come without drawbacks. Specifically, one of the disadvantages is the difficulty of exploiting external language models. Since the E2E models directly approximate the posterior token distribution, there is no straightforward way to integrate them, which generates recognition problems for rare events among other problems. These tail probability events cannot be expected to be comprehensively observed in training. The selection of the output units such as word pieces or characters instead of full words could theoretically mitigate these problems, but in practice this is not the case.

Several early attempts were proposed to integrate external language models (LM) into E2E systems, ranging from shallow or deep fusion, to cold fusion among others. In the ASR domain, shown that shallow fusion with same output units in both LM and E2E worked best to incorporate an external language model in some tasks. However, one of the disadvantages of shallow fusion comes from the fact that most of the E2E systems arguably already incorporate an internal LM. In this initial work, a density ratio approach was proposed to better integrate external LM by removing the internal LM contribution of E2E models while decoding. In this work, authors reported improvements over shallow fusion for domain adaptation tasks. Further works modified the architecture or made some assumptions to better approximate the implicit LM of E2E systems in combination with density ratio.

In many tasks, ASR systems are expected to recognize singletons or infrequent words such as contact list names or other named entities. These entities may not be seen during training, and even for those which are observed, the training data is clearly neither representative of the particular distribution nor of the relevant set associated with the application context for a given utterance. Consequently, even if the E2E model is using BPE or graphemenes as output units, the system struggles to recognize them. Several approaches have been introduced in the literature to contextualize E2E models to named entities such as song names or contact lists. In and , an additional attention set input is proposed for both attention and recurrent neural transducer (RNN-T) models respectively. Shallow fusion approach was applied surpassing state-of-the-art conventional models. More recently, shallow fusion was used in combination with special tokens to delimit class-based entity names together with a mapping to transform rare words to common words through pronunciation.

In this paper, we propose contextual density ratio for contextualizing E2E models so that the internal E2E LM is dynamically adapted to a priori known named entities. The proposed technique builds upon both density ratio and class-based LM tags to contextualize the E2E models. During training, we introduce special tokens to enclose known named entities so that the E2E system learns to predict when a named entity is spoken by the different statistical clues obtained from both the acoustics and the internal LM. We also approximate an internal E2E language model by training an independent LM with the transcriptions on which the E2E system was trained. During decoding, we apply density ratio within the named entities segments identified by the E2E model to dynamically adapt and contextualize the system’s LM. We show that the proposed contextual density ratio (CDR) reduces names recognition errors over a E2E baseline with and without contextual shallow fusion by 46.5% and 22.1 % respectively.

The paper is organized as follows. We first briefly review density ratio in section to pave the way for the following section where the proposed contextual density ratio is detailed. In section we apply the proposed technique to a doctor-to-patient conversation task for better recognizing both doctors and
patient names. Finally, in section 4 we conclude with some reflections.

2. Proposed approach

In this section we briefly summarize the contextual density ratio (CDR) approach. We first review the density ratio [15], and then we propose our extension to the contextual biasing scenario.

2.1. Density ratio (DR)

Neural network E2E models such as [1][20], directly approximate the probability of a target token sequence $y = y_1^t$, given acoustic features $x = x_1^T$, as follows:

$$p(y|x) \approx p_{\text{e2e}}(y|x)$$  \hspace{1cm} (1)

where $I$ is the length of the input acoustic features along time and $J$ the length of a possible token sequence; and where $p$ denotes the actual probability of the token sequence given the input acoustic features and $p_{\text{e2e}}$ the approximated model distribution.

In density ratio, we wish to adapt the posterior in-domain (ID) distribution $p(y|x)$ to a new out-of-domain (OOD) posterior, $q(y|x)$. Via standard noisy channel decomposition (Bayes’ law) and under assumption that acoustics of both domains are similar, $p(x|y) \approx q(x|y)$, we decompose the OOD posterior as:

$$q(y|x) = \frac{p(x|y)q(y)}{q(x)} = \frac{p(y|x)p(x)}{p(y)} q(x)$$  \hspace{1cm} (2)

Utilizing the same noisy channel decomposition for ID distribution $p(x|y)$ and rearranging terms, we obtain:

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)}$$  \hspace{1cm} (3)

Plugging eq 3 into eq. 2 yields:

$$q(y|x) = \frac{p(x|y)q(y)}{q(x)} = \frac{p(y|x) p(x)}{p(y)} q(x)$$  \hspace{1cm} (4)

Note that, eq. 4 has a marginal LM ratio $q(y)/p(y)$ and an acoustics density ratio $p(x)/q(x)$, which does not modify token sequences scores. We obtain the final density ratio (DR) approach by approximating distributions with models:

$$q(y|x) = p_{\text{e2e}}(y|x) \frac{q_{\text{ood}}(y)}{p_{\text{ood}}(y)} \frac{p(x)}{q(x)}$$  \hspace{1cm} (5)

which approximates the acoustic distribution with both an ID language and E2E models, $p_{\text{ood}}$ and $p_{\text{e2e}}$; and shifts the posterior with an OOD language model, $q_{\text{ood}}$, up to a constant ratio on the acoustics. Note that $p_{\text{ood}}$ corresponds to the marginal distribution obtained from E2E posterior, $p_{\text{e2e}}$; in practice we take the E2E model training transcriptions as approximately sampling from this distribution.

Finally, when performing the beam search we apply weights to balance out the importance of each score, yielding the search score:

$$\text{score}(y,x) = \log p_{\text{e2e}}(y|x) - \alpha \cdot \log p_{\text{ood}}(y) + \beta \cdot \log q_{\text{ood}}(y)$$  \hspace{1cm} (6)

2.2. Contextual density ratio (CDR)

Density ratio (DR) [15] can bias the distribution for the full utterance, but we would like to adapt the language model of E2E systems to be able to recognize named entities such as contact list names, or client names. These named entities may occur at any position inside a utterance and often only span a few words.

In order to do so, we extend the token vocabulary with special words for both start and end of entities, $<\text{ne}>$ and $<\text{/ne}>$.

During training, our E2E model inserts those tags in between known named entities, for instance, the _next_ patient _<ne> be e th o ve n_ _<ne>/ne> is _<ne>_ losing _his_ _<ne>/ne> hearing _<ne>. The system learns to predict when those named entities will occur, and during beam search or decoding, the system hypothesizes those special tokens as if they were standard tokens. Although we focus on a single tag for simplicity in this work, we could add as many specialized tags as desired.

In the previous section, we reviewed the DR approach for full utterance biasing. However, in practice, each token distribution on eq. 5 is approximated autoregressively as follows:

$$q(y|x) = \prod_{t=t_0}^{t=t_1} p_{\text{e2e}}(y_t|x, y_{<t}) \frac{q_{\text{ood}}(y_t)}{p_{\text{ood}}(y_t)} \frac{p(x)}{q(x)}$$  \hspace{1cm} (7)

Because of the new tokens added to the E2E vocabulary, we know the positions where the named entities will occur. For simplicity, we assume a single named entity occurrence at position $(t_b, t_e)$. Then, the token posterior probability of an utterance with a named entity is decomposed by:

$$q_{\text{ne}}(y|x) = \prod_{t=t_0}^{t=t_1} p_{\text{e2e}}(y_t|x, y_{<t}) \frac{p_{\text{ne}}(y_t)}{p_{\text{ne}}(y_t)} \frac{p(x)}{q(x)}$$  \hspace{1cm} (8)

where recall $y_t = <\text{ne}>$. Note that the in-domain (ID) and named entity (NE) LMs condition on different context. It is worth mentioning that the acoustic density ratio, $p(x)/q(x)$, may introduce a bias when comparing hypotheses with different number of named entities. However, assuming acoustics are similar, this ratio should approach 1 and we verified in the next section that this is not a problem in practice.

During beam search or decoding, each token is scored with $\text{score}(y_t) := \text{score}(y_t; y_{<t}, x)$ computed as:

$$\text{score}(y_t) = \begin{cases} \log p_{\text{e2e}}(y_t|... + \log \frac{q_{\text{ood}}(y_t|y_{<t})}{p_{\text{ood}}(y_t|y_{<t})}, \text{ne}(y_{<t}) \\
\log p_{\text{e2e}}(y_t|...), \text{otherwise} \end{cases}$$  \hspace{1cm} (9)

where we omit $y_{<t}, x$ from $p_{\text{e2e}}(y_t|...$. The notation $\text{ne}(y_{<t})$ indicates whether there is an open named entity tag in the previous tokens that has not yet been closed and in such a case, $t_b := t_b(y_{<t})$ is the position of the start tag token, $<\text{ne}>$. In practice, LM distributions are weighted by $\alpha$ and $\beta$ to smooth them.

Figure 1 depicts a small segment of an utterance with a named entity. The E2E model scores each token independently of whether it is within a named entity tag, in contrast to both
We trained the language model with truncated backpropagation trained, together with the very same for the contextual density ratio technique, we use the exact for the contextual density ratio technique. The ID LM, is tracking full context from the beginning of the utterance in contrast with the NE LM which accounts for a total of 31.99M parameters. We regularized the model with small weight-decay and dropout. For decoding, both the \( \alpha \) and \( \beta \) parameters were tuned on a different domain adaptation density ratio setup and both equal to 0.1. This ensures that search parameters are not over-trained to the specifics of the contextual density ratio task or the test set. In addition, because of the attention models, we used a coverage score \( \frac{a_1^2}{a_1^2} \) of 0.3 optimized in conjunction with \( \alpha \) and \( \beta \).

For the contextual LMs, we initialized them with the same in-domain LSTM based language model and trained them until convergence on the specific list of names extracted per each conversation.

### 3.3. Results

In order to measure the different systems, we report the word error rate (WER), as well as the WER within the name tags (WERT). This allows us to evaluate both overall performance of the system as well as the specific improvements on name recognition.

First, we trained both an E2E baseline model without tags and an E2E model with the name tags (\( \text{<ne>} \) and \( \text{/ne>} \)). Second line of Table 1 shows that adding the tags slightly hurts the model performance, compared to the first line, but the difference is small and within training repetition variance (+/- 0.1). Then, we added contextual biasing by either shallow fusion or contextual density ratio in the realistic scenario, in which we build a context biasing language model per conversation. As reported in the last 2 lines of Table 1 in both cases, we recover part of the small drop in accuracy while significantly improving name performance. Adding a contextual biasing shallow fusion component reduces name errors by 31.3 % relative. Contextual density ratio biasing reduces name errors by 46.5 % relative with respect to the E2E baseline and 22.1 % compared to shallow fusion. Note that if all names were wrongly recognized by substitutions, this will account for only 0.43% of the whole test set WER.

Table 2 compares the precision and the recall on the contextual tags themselves for the 3 systems with tags from Table 1. Both contextual density ratio and contextual shallow fusion improve the tagging precision and recall over the baseline, with contextual density ratio being better than contextual shallow fusion. The improvements in terms of precision and recall are small compared to the WERT improvements from Table 1 and consequently the name WERT improvement cannot be attributed as a side effect of better tagging. We hypothesize
Table 1: Word Error Rate (WER) and Word Error Rate within the named entities Tags (WERT) for several systems. Both contextual systems based on either SF or DR, extend the E2E model with contextual tags and are based on full conversations.

| System                          | WERT | WERT  |
|---------------------------------|------|-------|
| E2E without contextual tags    | 14.94| n.a.  |
| E2E with contextual tags       | 15.10| 44.1  |
| + contextual SF                | 15.04| 30.3  |
| + contextual DR (CDR)          | 15.00| 23.6  |

Table 2: Precision and recall computed on the contextual tags themselves for the different contextual systems on Table 1.

| System                          | Precision | Recall  |
|---------------------------------|-----------|---------|
| E2E with contextual tags        | 78.5      | 79.4    |
| + contextual SF                 | 80.7      | 82.6    |
| + contextual DR (CDR)           | 82.0      | 83.5    |

Table 3: WERT precision and recall for a single LM per utterance (oracle case) and a single LM for the full test set dropping conversation level information.

| System                  | WERT | Precision | Recall |
|-------------------------|------|-----------|--------|
| 1 LM per utterance (Oracle) | 20.1 | 82.6      | 85.1   |
| 1 LM for full test set   | 37.3 | 78.5      | 79.7   |

Table 4: WERT for 16 names with different Levenshtein distances, applied to per-conversation CDR case.

| Levenshtein distance | WERT | Precision | Recall |
|----------------------|------|-----------|--------|
| random               | 23.9 | 28.2      | 30.5   |
| 4                    | 2     | 30.5      | 28.3   | 4

Figure 2: WERT (y-axis) at increasing number of per-conversation randomly sampled distracting names (log-scale).

4. Conclusions

In this paper, a contextual density ratio for contextual language model biasing was proposed. This technique was applied to the task of name recognition in doctor-patient conversations. The proposed approach improves name recognition up to 46.5% with respect to a standard E2E system or 22.1% relative with respect to contextual shallow fusion. Moreover, the technique does not degrade the system performance on utterances without names significantly and has no major side effects.

The behaviour of the proposed technique was studied by adding random distracting and adversarial names to the biasing name list. Contextual density ratio is robust to noise, being more sensitive to similar names. As future work, we want to improve the technique in those adversarial conditions, for instance by also taking into account the phonetics.

5. References

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