TEXT AUGMENTATION FOR LANGUAGE MODELS IN HIGH ERROR RECOGNITION SCENARIO

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ABSTRACT

We examine the effect of data augmentation for training of language models for speech recognition. We compare augmentation based on global error statistics with one based on per-word unigram statistics of ASR errors and observe that it is better to only pay attention the global substitution, deletion and insertion rates. This simple scheme also performs consistently better than label smoothing and its sampled variants. Additionally, we investigate into the behavior of perplexity estimated on augmented data, but conclude that it gives no better prediction of the final error rate. Our best augmentation scheme increases the absolute WER improvement from second-pass rescoring from 1.1% to 1.9% absolute on the CHiMe-6 challenge.

Index Terms— data augmentation, error simulation, language modeling, automatic speech recognition

1. INTRODUCTION

The traditional reason language models (LMs) appear in ASR systems is that they directly represent the prior term \( P(S) \) in the Bayes factorization of the posterior probability \( P(S|A) \) of a sentence \( S \) given the audio \( A \). However in practice, LMs trained on excessive amounts of data are combined with hybrid and end-to-end systems alike \[1,2,3\] at authors liberty. Overall, LMs can be seen as a refinement tool to apply on a preliminary result of recognition.

To this end, language models can be trained to cope with errors introduced during the first phase of ASR. This is especially well pronounced in discriminative LMs \[4,5,6\], which focus on obtaining the final hypothesis from a pool of first-pass hypotheses, oftentimes explicitly taking acoustic clues into account. On the other hand, we have recently achieved interesting improvements by simply augmenting the training data for a conventional generative LM \[7\].

The idea of working with data similar to ASR output is not new: Errors are typically introduced in the form of substitutions, driven by a custom confusability measure \[8\]. Recently, sequence-to-sequence models have been proposed for the task \[10\].

In this work, we elaborate on our central idea that an LM should be capable of good predictions of the next word even when it is exposed to some mistakes in the history: We extend the idea of augmenting data from substitutions only to deletions as well as insertions. Then, we investigate the source of improvement by comparing this well-motivated input augmentation to target augmentation. Finally, we examine the change of the perplexity implied by the data augmentation.

2. SIMULATING THE ERRORS

In the traditional setting, language models are trained to maximize the probability of the word \( w_t \) at any position \( t \) in the text, as conditioned on the history \( h_t \) comprising all previous words \( w_1 \ldots w_{t-1} \):

\[-\log PPL = \frac{1}{T} \sum_{t=1}^{T} \log p(w_t|h_t) \quad (1)\]

In this study, we expose the LM to erroneous \( h_t \), similar to what it experiences when processing output from an ASR system, giving rise to simulated PPL:

\[-\log sPPL = \frac{1}{T} \sum_{t=1}^{T} E_{\hat{h}_t \sim p_{\text{ASR}}(h_t)} \left[ \log p(w_t|\hat{h}_t) \right] \quad (2)\]

We discuss the approximations of \( p_{\text{ASR}}(h_t) \) in Section 2.1. In general, the input history \( h_t \) is processed token by token and individual edits are introduced as illustrated in Fig. 1. We take care not to remove, replace or introduce sentence boundaries.

We also introduce target augmentation to check that the LM benefits from modeling of ASR errors rather than simply from regularization by adding noise to the data. Target augmentation differs in that when introducing substitutions, we keep the input token and replace the target one. Contrasting this to the simulated perplexity (omitting deletions and insertions), we arrive at:

\[1\] Due to a bug in the implementation, we provided no special care to sentence breaks initially. Despite being theoretically unsound, it did not have any observable impact.
it's
it's
good
bad
salad
salad

(a) Substitution

(b) Deletion

(c) Insertion

Fig. 1: How errors are introduced for NN LMs. The original sentence is “it’s good salad”. With substitution (a), only the input token is replaced. To simulate deletions (b), both the input and the target at the given position are removed. Finally, inserted words (c) get into the input while the original target token gets duplicated.

2.1. Error simulating distribution

As a baseline for error simulation, we do the sampling in a truly flat manner: We simply roll an unfair 4-sided dice to determine which of the four actions to take. In case substitution or insertion should be done, we take a sample from uniform distribution over the vocabulary to obtain the new input token. We call this the 0-gram error model. By adjusting the initial categorical distribution (the dice), we have a fine control over the strength of the data augmentation.

In order to better match the actual errors made by the first-pass recognizer, we propose a stronger, 1-gram, model. We prepare it as follows: For a given set of utterances, we get the 100-best hypotheses from the ASR system. Secondly, we align these hypotheses to the actual transcriptions of this data. Then for each reference word \(w_{act}\), we summarize its alignments over the whole data and normalize the counts of hypothesised words to get the distribution \(p_{sub}(w|w_{act})\). This categorical distribution is then used to decide the action to apply on every training token. Note that by treating the empty symbol \(\varepsilon\) as a regular word, we also naturally model insertions and deletions this way. In the case of 1-gram error models, the overall rate of substitutions, deletions and insertions is given by the statistics themselves.

3. EXPERIMENTS

We evaluate the proposed techniques on Track 1 of the CHiMe-6 challenge \[11\]. The size of training and development data, including sentence boundaries, is 522k and 136k tokens respectively. For ease of implementation, we stay with the official large vocabulary of 127k words, letting the output softmax layer to learn that many of those do not occur in the training data.

As the ASR to provide inputs for this paper, we used a single Kaldi system based on a mix of CNN and TDNN-f layers. The first-pass decoding network is based on a KN-smoothed 3-gram LM. For further details on the design of the ASR system, refer to the system description \[7\].

This system achieves 48.39 % WER on the development data. The error is composed respectively of 5 %, 17 % and 26 % of insertions, deletions and substitutions.

For any LM evaluated, we extract 3000-best hypotheses to rescore and use the development set to tune the linear interpolation coefficient for mixing the LSTM LM with the first-pass 3-gram LM. When rescoring, we carry the hidden states over, except for session breaks. This way, we effectively model the language across segments \[12\].

3.1. Language Model Training

In all our experiments, we use two layer LSTM \[13\] with 650 units per layer and the dimensionality of input word embeddings reduced to 100. We train our language models in \(\text{BrnoLM}^{2}\).

We train the LMs with plain SGD, in two stages: At first, we train the LM from scratch with shuffled lines. In this stage, we always employ the data augmentation technique under test. Secondly, we take the trained LM and finetune it on the sentences in their original order. We ran this stage twice, with this augmentation turned either on or off. It was always slightly better to do this finetuning with clean data, thus we only report these results.

We begin the first phase training with learning rate 2.0 and start the finetuning with 0.2, in both stages halving the learning rate when development perplexity does not improve. With target augmentation, we observed the training to be more noisy, therefore we only halved the learning rate when no improvement was observed for 3 consecutive epochs.

3.2. Tested Augmentation Schemes

In total, we test LMs trained with seven augmentation schemes:

\[^{2}\text{https://github.com/BUTSpeechFIT/BrnoLM}\]
1. The **baseline**, which is only trained on the actual training transcripts.

2. the 0-gram model (i0), which is trained with uniformly sampled errors. With this model, we optimize for the best rate of substitutions, deletions and insertions.

3. the 1-gram model (i1), where we collect the statistics from the training data.

4. the oracle 1-gram model (i1o), where the statistics are collected from the development data.

5. a 0-gram target augmentation (t0S), where we only introduce substitutions, at the rate optimal for input augmenting systems.

6. a 0-gram target augmentation (t0SDI), where we introduce deletions and insertion in addition to the target substitution.

7. target label smoothing (t0LS) \[14\]. Note that unlike the other techniques, label smoothing requires a principally different change of the training procedure.

For all augmentation schemes, we sweep across the rate of dropout in range \([0.0, 0.7]\) to find the optimal level of total regularization. For the baseline, the best result comes from setting it to 0.7\(^3\), those trained with data augmentation were fairly robust to the dropout rate and achieved their best performance in range of 0.3 – 0.6.

### 3.3. CHiMe-6 Rescoring Results

We first assess the performance on the development data, as captured in Figure 2. Overall, we see that the behavior of all LSTM LMs is smooth with respect to the interpolation coefficient.

The best performance is achieved by the input 0-gram augmentation. For this augmentation, we have found values of around 0.23, 0.15 to work the best as the substitution and deletion rate respectively. Insertions did not provide any measurable improvements up till 0.1; higher values caused degradation. This suggests that the input augmentation should roughly correspond to the actual errors rates (see Sec. 3).

On the other hand, neither input 1-gram augmentation was significantly better than the baseline. The target augmenting LMs do achieve improvement over the baseline, albeit smaller than the 0-gram input augmentation. Introduction of deletions and insertions brought no improvement for the target 0-gram augmentation, however we have observed these LMs to be rather insensitive to the rate of dropout.

In Table 1, we capture the performance of the models on the unseen evaluation data. We can see that the overall behavior of individual systems stays similar and the input 0-gram augmentation brings clearly the largest gain.

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\(^3\)In this case, we tried higher values to check it is the optimum.
Table 1: Results of rescoring ASR outputs with LMs trained with different data augmentation schemes. We report the result of the optimal setting of dropout and LSTM-LM weight as per development results.

|                      | development | evaluation |
|----------------------|-------------|------------|
| 3-gram only          | 48.39       | 48.82      |
| baseline             | 46.86       | 47.69      |
| input 0-gram         | **46.05**   | **46.92**  |
| input 1-gram         | 46.85       | 47.70      |
| input 1-gram oracle  | 46.82       | 47.97      |
| target 0-gram S      | 46.20       | 47.41      |
| target 0-gram SID    | 46.20       | 47.23      |
| target label smoothing| 46.43       | 47.70      |

3.4. Experiments on Firefighter Speech Recognition

During the work on this paper, we have applied the 0-gram input augmentation to speech recognition in the OpenSAT challenge [15]. This task is considerably easier, with WER at around 10%. By adding the augmentation, we have achieved a marginal gain of about 0.1% absolute, confirming our hypothesis that this method brings benefit mainly when employed in high error scenarios.

3.5. Behavior of the Simulated Perplexity

Since the best performing LMs are trained with the sPPL objective, we investigate two of its properties. Firstly, we observe its stability as we only estimate the expectation in (2) from a single realization of noise. In doing so, we inspect behavior of two different LMs, where one was trained to optimize sPPL and the other regular PPL. Then we examine the predictive power of sPPL towards the final WER of the system.

The stability is captured in Figure 3. The sPPLs are approximately normally distributed, with relative standard deviation of around 0.5%. Comparing the baseline LM to the one trained on the augmented data, we see that the baseline has significantly higher average sPPL (226.5 vs. 178.7) and a slightly higher standard deviation.

To assess the predictive power of sPPL, we plotted a couple of i0 LMs as described by their development (s)PPL and WER in Figure 4. We did not find any conclusive evidence that sPPL would serve as a better predictor than PPL.

4. CONCLUSIONS

We have examined several simple text data augmentations for language model training. Evaluating them by rescoring ASR outputs on the CHiMe-6 challenge, we have achieved the best result when simply introducing uninformed edits into the stream of input tokens. This improved the WER by 0.8% absolute over rescoring with the baseline LM given by the same neural architecture, but trained on clean text only. No improvements were achieved with augmentation based on the actual word level confusions produced by the ASR system. Finally, a control experiment with target augmentations reached approx. 0.5% abs. improvement. From these experimental results, we conclude that while the LMs do benefit from being exposed to ASR-like errors, most of the improvement is coming from training on noised data per se.

We also investigated into the properties of simulated perplexity (sPPL) estimated on the augmented data. While being rather stable w.r.t. the sampling of the word-level noise, we did not see sPPL predict the WER any better than PPL. Furthermore, we always obtained better results when finetuning the LMs to clean data, solidifying our belief that the proposed augmentation scheme should be viewed as a successful regularization technique rather than as an adaptation to a given ASR system.

5. ACKNOWLEDGEMENTS

We thank Martin Kocour for providing the CHiMe-6 ASR system outputs.
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