Homophone-based Label Smoothing in End-to-End Automatic Speech Recognition

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Abstract

A new label smoothing method that makes use of prior knowledge of a language at human level, homophone, is proposed in this paper for automatic speech recognition (ASR). Compared with its forerunners, the proposed method uses pronunciation knowledge of homophones in a more complex way. End-to-end ASR models that learn acoustic model and language model jointly and modelling units of characters are necessary conditions for this method. Experiments with hybrid CTC sequence-to-sequence model show that the new method can reduce character error rate (CER) by 0.4% absolutely.

Index Terms: automatic speech recognition, homophone label smoothing

1. Introduction

An intuitive way to generate the distribution from training data is one-hot distribution in which only the class given by ground truth is assigned with probability of 1. While other classes are assigned with probability of 0. Training a network with one-hot distribution can cause over confidence in the networks output distribution. Over confidence of a network indicates that the networks structure is less smoothing and can do harm to its ability of generalization.

One method to solve over confidence problem is to generate a new distribution by adding one-hot distribution with a prior distribution and to learn the network with the new distribution. This method is called label smoothing (LS). Another way to solve over confidence problem is output regularizers: a negative log-likelihood loss function. Furthermore, distillation exploits the idea of training a small network with distribution given by a large network by assuming that larger networks have better generalization. The problem is still that it is hard to train large networks when dataset is small.

We will concentrate on the LS methods in this paper. The uniform and unigram LS strategy have been introduced and implemented for ASR. Uniform LS assigns same probability 1/K to all characters, where K is number of characters as modelling units. Unigram LS assigns the probability of a character by its character frequency in the training dataset. Both LS methods use the prior knowledge of language at shallow level. To the best of our knowledge, no further prior knowledge of language have been used to generate the prior distribution.

Homophones exist in Chinese, Japanese and Korean. In this paper, we consider the application of label smoothing in ASR by making use of deeper prior knowledge: homophone.

1.1. The sequence-to-sequence ASR models

Encoder-decoder based sequence-to-sequence (seq2seq) models with attention mechanism have shown state-of-the-art performance in ASR. A hybrid CTC-seq2seq model is introduced in [3]. In this hybrid structure, CTC together with seq2seq can enforce monotonic alignment between speech and label sequences. The discussion in this paper concerns on the seq2seq structure that is composed of RNN-like encoder and decoder. One critical feature of the seq2seq model is that it can combine acoustic model (AM) and language model (LM) together.

Denoting the variable length T input frames as x = (x1,...,xT), U length output characters sequence as c = (c1,...,cU), cu ∈ {1,...,K}, where K is the number of characters, which are modelling units.

The seq2seq model predicts label distribution at position u conditioning on the previous labels by the following recursive procedures [5][6].

\[ p(c_u|c_{1:(u-1)}) = \prod_u p(c_u|c_{1:u-1}). \] (1)

With cu, su−1 and au, the decoder can generate next label cu and update the status as following,

\[ c_u = \text{Generate}(a_u, s_{u-1}), \] (2)

\[ s_u = \text{Recurrency}(s_{u-1}, a_u, c_u), \] (3)

where su−1 is the decoder status and au is the content of input given by attention mechanism [5][6]. Combining equation (2) and (3), one obtains

\[ c_u = \text{Generate}(a_u, \text{Recurrency}(s_{u-2}, s_{u-1}, c_{u-1})). \] (4)

When the ground truth c∗ is given, the loss function of the seq2seq model can be computed as

\[ \mathcal{L} (\theta, c^*) \triangleq - \log p(c^*|x) = - \sum_u \log p(c_u|c_{1:u-1}). \] (5)

where c_{1:u-1} is the ground truth of the previous characters and θ is the parameters of seq2seq model.

1.2. Analysis to distribution problems of homophones

To analyze the distribution of homophones generated from training corpus, let us consider two pairs of training data (x¹, c¹), i = 1, 2, where c¹ = (c¹₁,...,c¹_U) and c²_u = c²_u for u = 1,...,U. We assume further that c²_{u+1} is a homophone of c¹_{u+1}, i.e., c²_{u+1} and c¹_{u+1} have same pronunciation.

Given the fixed pair (x¹, c¹), we consider equation (4) with respect to c²_{u+1} and c¹_{u+1} respectively at position u = U + 1, then obtain

\[ c²_{U+1} = \text{Generate}(a²_{U+1}, \text{Recurrency}(s¹_{U-1}, a²_U, c²_{U})). \] (6)
\[ c_{U+1} = \text{Generate}(c_{U+1}^2, \text{Recurcy}(c_{U-1}^1, a_U^1, c_U^1)). \] (7)

It is easy to see that the following probability equation with respect to \( c_{U+1}^1 \) and \( c_{U+1}^2 \) holds

\[ p(c_{U+1}^1 | x^1, c_U^1) = p(p(c_{U+1}^2 | x^1, c_U^1), \] (8)

since the input terms \( a_U^1, a_U^2 \) and \( s_U^1 \), on the right side of \( [6] \) and \( [7] \) are identical. Identity of \( s_{U-1}^1 \) in the two equations can be concluded from equation \( [3] \) and the assumption of \((x^2, c^2)\). Similar analysis to \((x^1, c^1)\) can result in

\[ p(c_{U+1}^2 | x^2, c_U^2) = p(p(c_{U+1}^2 | x^2, c_U^2), \] (9)

If one generates distribution from \((x^1, c^1)\) without LS or with simply LS, the assigned probability \( p(c_{U+1}^2 | x^1, c_U^1) \) is significantly higher than the assigned probability \( p(c_{U+1}^2 | x^2, c_U^2) \) (saying the probability of \( c_{U+1}^2 \) is not distinguishable from other characters that are not homophones of \( c_{U+1}^2 \)) within training data pair \((x^1, c^1)\), i.e.,

\[ p(c_{U+1}^2 | x^1, c_U^1) \gg p(c_{U+1}^2 | x^2, c_U^2). \] (10)

Similar analysis to \((x^2, c^2)\) results in

\[ p(c_{U+1}^2 | x^2, c_U^2) \ll p(c_{U+1}^2 | x^2, c_U^2). \] (11)

Equation \( [8] \) and \( [10] \) contradict with each other, equation \( [9] \) and \( [11] \) contradict with each other too.

Furthermore, considering \( c_{U+1}^1 \) equals with \( c_U^2 \), the only difference between the left hand side of \( [8] \) and that of \( [10] \) is the difference between \( x^1 \) and \( x^2 \). But the left hand side of \( [9] \) and that of \( [11] \) are assigned with very different probability. This will cause the AM to overfit to the slight input features difference between \( x^1 \) and \( x^2 \), considering that \( x^2 \) and \( x^2 \) share most of phonetic information, in form of FBank features, which is useful for ASR \((x^1, c^1)\) and \( (x^2, c^2)\) share same pronunciation.

To alleviate this phenomenon, we propose a new LS strategy based on homophones to make the following equation holds

\[ p(c_{U+1}^2 | x^2, c_U^2) \approx p(c_{U+1}^2 | x^2, c_U^2), \]

for \((x^1, c^1), i = 1, 2\). The new LS strategy can help to generate smoothing distribution for homophones in general cases.

To sum up, two basic conditions are required to make homophone label smoothing work:

- The ASR model should be an end-to-end one that learns AM and LM jointly and simultaneously.
- The modelling units should be characters, i.e., the modelling units should be at the level where the homophone phenomenon takes place.

2. Homophone-based label smoothing

2.1. Over confidence penalty by KL divergence

Let us first introduce label smoothing in ASR. For position \( u \), instead of learning the one-hot distribution \( v_{OH}^u(y_u) \) in which \( c_u^u \) is the ground truth at \( u \), one can train the networks with the following label smoothing distribution

\[ p'(y_u) = (1 - \beta) v_{OH}^u(y_u) + \beta v(y_u), \] (12)

where

\[ v_{OH}^u(y_u, k) \triangleq \begin{cases} 1, & \text{if } k = c_u, \\ 0, & \text{others}, \end{cases} \] (13)

is the one-hot distribution and \( k_0 \) is the index of \( c_u^u \) in \( \{1, \ldots, K\} \).

When the prior distribution \( v \) is given and considering the position \( u \), networks learning with smoothing distribution \( p' \) is equivalent to adding KL divergence between the distribution \( v \) and the networks output distribution \( p \) to the negative log-likelihood \( [1][2] \). It deserves to point out that the negative log-likelihood is cross entropy between one-hot distribution and networks’ output distribution. It results in, together with the single term of \( u \) in right hand side of equation \( [5] \), a new loss function at position \( u \) with respect to the training data pair \((x, c^*)\)

\[ L(\theta, c_u^*) = -(1 - \beta) \log p(c_u^* | x, c_{u-1}^u) + \beta \mathcal{D}_{KL}(v(y_u) \| p(y_u | x, c_{u-1}^u)), \] (14)

in which we use notation \( v(y_u) \) to indicate that the distribution is not connected with \( c_u^* \), \( y_u = (y_{u,1}, \ldots, y_{u,K}) \) is the vector of random variables over all characters at position \( u \). The parameter \( \beta \) is for the trade off between the negative log-likelihood and KL divergence penalty term.

As discussed in last chapter, one can make use prior language knowledge, homophone, to generate distribution \( v(y_u) \) such that it depends on \( c_u^* \), i.e. \( v(y_u) \triangleq v_{OH}(y_u) \), in which the subscript \( c_u^* \) indicates that the prior distribution \( v_{OH}(y_u) \) is related to \( c_u^* \). With \( v(y_u) = v_{OH}(y_u) \) holds, equation \( [14] \) becomes

\[ L_{HOMO}^{\text{LS}}(\theta, c_u^*) = -(1 - \beta) \log p(c_u^* | x, c_{u-1}^u) + \beta \mathcal{D}_{KL}(v(y_u) || p(y_u | x, c_{u-1}^u)). \]

Correspondingly, the loss function of seq2seq model with homophone-based prior distributions for sequence \( c^* \) is

\[ L_{HOMO}^{\text{LS}}(\theta, c^*) = -(1 - \beta) \sum_u \log p(c_u^* | x, c_{u-1}^u) + \beta \sum_u \mathcal{D}_{KL}(v_u(y_u) || p(y_u | x, c_{u-1}^u)), \]

in which KL divergence is defined as

\[ \mathcal{D}_{KL}(v_u(y_u) || p(y_u | x, c_{u-1}^u)) = -\sum_k v_{OH}(y_u, k) \log \frac{p(y_u, k | x, c_{u-1}^u)}{v_{OH}(y_u, k)}. \]

It will be described in next subchapter how to generate the prior distribution \( v_{OH}(y_u) \).

2.2. Prior distribution by homophones

2.2.1. Homophone with unigram based prior distribution

In application, considering that \( c_u^* \) can either has homophones or not, the prior distribution \( v_{OH}(y_u) \) can be defined correspondingly as

\[ v_{OH}^u(y_u, k) \triangleq \begin{cases} v_{\text{HOMO}}^u(y_u), & \text{if } c_u^* \text{ has homophone(s)}, \\ v_{\text{UNIQ}}^u(y_u), & \text{if } c_u^* \text{ has no homophone(s)}. \end{cases} \] (15)

where \( v_{\text{UNIQ}}^u(y_u) \) is unigram distribution generated from training corpus.
2.2.2. Homophone with N-gram based prior distribution

The homophone label smoothing strategy can be improved further by taking more complex contextual information into consideration. In this way, the prior distribution can be defined as following

$$v^K_{HOMO}(y_u) \triangleq \begin{cases} v^K_{CL}(y_u) & \text{if } c^*_{u} \text{ has homophone(s),} \\
0 & \text{if } c^*_{u} \text{ has no homophone(s),} 
\end{cases}$$

where $v^K_{CL}(y_u)$ denotes the label smoothing distribution than can be defined by a N-gram LM, which can be trained with a larger text corpus individually. The meaning of the distribution $v^K_{CL}(y_u)$ is the distribution over all characters at position $u$ according to the previous $N-1$ characters. The distribution has nothing to do with $c^*_{u}$ itself, the subscript $c^*_{u}$ is only for the consistency of symbols.

To define $v^K_{HOMO}(y_u)$, we consider arbitrary position $u$ and its corresponding ground truth character $c^*_{u}$. Considering that $c^*_{u}$ has homophones, we denote the set of characters which are homophones of $c^*_{u}$ as $\text{Homo}(c^*_{u})$, whose size is $N$. Denoting $k_0$ as the index of $c^*_{u}$ in the set $\{1, \cdots, K\}$ and $\text{Homo}(k_0)$ as the set of indexes of elements of $\text{Homo}(c^*_{u})$ in set $\{1, \cdots, K\}$, the homophone-based distribution $v^K_{HOMO}(y_u)$, in which $y_u = (y_{u,1}, \cdots, y_{u,K})$, can be defined as

$$v^K_{HOMO}(y_{u,k}) \triangleq \begin{cases} 0.6 & \text{if } k = k_0, \\
\frac{0.2}{N} & \text{if } k \in \text{Homo}(k_0), \\
\frac{0.3}{K-N+1} & \text{Others.} 
\end{cases},$$

One would notice that $\text{Homo}(c^*_{u})$ is not only determined by character $c^*_{u}$ itself, but also by its pronunciation. The pronunciation of $c^*_{u}$ is determined by tokenization of the sentence, since $c^*_{u}$ could be a polyphone. To choose right pronunciation for $c^*_{u}$ and determine $\text{Homo}(c^*_{u})$, one must make right tokenization first, when we take Chinese language into consideration.

To sum up, the homophone-based label smoothing strategy contains two steps: 1. generating homophone-based prior distribution. 2. training neural networks with prior distribution.

3. Experiments

The toolbox Espnet [4], together with Chinese language, are used for experiments. The modelling units are 6763 Chinese characters selected from level I and II of GB2312, 54 English letters (uppercase and lowercase), (UNK) and (space).

A composite corpus, which includes AISHELL-2 and some other smaller corpus, is used for the experiments. The corpus is of 1499 hours and is of about 1.5 million utterances, in which the test set is 3.9 thousand utterances. The reason for the relatively smaller test dataset is that the decoding with non-streaming hybrid CTC-seq2seq model is slow.

3.1. Settings

The encoder consists of CNN and LSTM [7]. The LSTM-related part of encoder consists of 3 layers with 1024 units each. The projection units of LSTM is 1024.

The decoder is of 2 layer LSTM with 1024 units each.

The attention mechanism used is content and location aware one [5]. For the attention, the number of attention convolution channels is 10, and the number of attention convolution filters is 100. The dimension of attention is 1024.

For training, the weight for CTC is $\lambda = 0.5$, weight of KL divergence is $\beta = 0.4$, dropout parameter is set to 0.5. It de- serves to point out that it takes more epochs for homophone LS to reach its best model, comparing with the non-LS model. The non-LS model reaches its best model at 8th epoch, while homophone LS takes 23 epochs to reach its best model, under the same optimizer configuration. One can choose one-hot distribution at beginning of training to speed up convergence and apply homophone-based LS at end of training to guarantee better generalization [1], but this experiment is not conducted in this paper.

For decoding, the weight for CTC is $\lambda = 0.6$, beam search size is set to 20. The decoding test is without shallow fusion LM. One can download the source code from “https://github.com/zhengyiuestc” to check for more details.

Several LS experiments are implemented with the same network configuration above: non-LS, unigram LS, homophone with unigram LS and homophone with bigram LS. The unigram distribution is generated by the text of training corpus. The N-gram LM is chosen to be the bigram LM, which is trained on the CLUECorpus2020 corpus with KenLM tool [9].

The results in Table 1 indicates that homophone LS can reduce CER by 0.4% absolutely comparing to its best competitor non-LS.

| Methods                      | CER test |
|------------------------------|----------|
| Non-LS                       | 7.9%     |
| Unigram LS                   | 9.5%     |
| Homophone with unigram LS    | 7.5%     |
| Homophone with bigram LS     | 8.8%     |

4. Conclusions

The experiment results indicate that the performance of seq2seq ASR models can be improved if the human-level prior language knowledge, homophone, is injected via label smoothing. Though distillation idea can use the knowledge of larger networks to teach the smaller networks, the larger networks can not necessarily learn the prior knowledge at human’s level. More ASR models with different structures will not be conducted in this paper but left as further discussion in next chapter.

5. Further discussion

To consider the model structures, besides seq2seq structure, homophone LS can be applied in transformer-based and CTC-like ASR models. Further more, we discuss the possibility of apply homophone LS in on-streaming seq2seq and on-streaming transformer ASR models. With regarding to LM, we consider to introduce the N-gram term to replace the unigram term in [15] with the aim to make use of broader text information. At the end, the influence of homophone LS to decoding paths selection is analyzed based on seq2seq models which are shallowly fused with recurrent neural network LMs (RNN-LMs).

5.1. Other ASR model structures

5.1.1. Transformer-based ASR models

Transformer-based ASR models have shown their state-of-the-art performance recently [10]. Since the new idea of this pa-
per has only impact on the training distribution, one can apply the same analysis to transformer-based ASR models and obtain similar results.

5.1.2. CTC-like Model

If one considers the CTC part of the hybrid CTC-seq2seq network, it is composed of the encoder and CTC loss function. Noticing that the encoder has been restricted by label smoothing strategy via seq2seq part of the hybrid network during multi-task training, the performance of CTC decoding model, which takes the same encoder together with WFST language model \cite{11}, will be improved from the new label smoothing strategy.

5.2. On-streaming ASR models

The on-streaming hybrid CTC-seq2seq structure and on-streaming transformer structure can also benefit from the new idea \cite{12,13}. Comparing with non-streaming models, the main difference in on-streaming models is the conditional distribution in equation (1). This says the condition dependency in (1) and its followed equations is no longer depends on the whole input sequence \( x \) but part of \( x \).

5.3. LM shallow fusion

5.3.1. Paths selection with LM shallow fusion

Homophone LS can benefit the paths selection in one-pass decoding where on-streaming ASR models are shallowly fused with RNN-LMs \cite{13}, when one considers the on-streaming hybrid CTC-seq2seq model and the on-streaming transformer model \cite{12,13}.

Considering the probability accumulation of AM and LM during one-pass decoding procedure where the AM is not trained with homophone LS, if a wrong homophone is chosen with high probability by seq2seq model, it will be hard for LM to correct the error by accumulating AM and LM scores together. Because the probability difference between right and wrong homophone is too high. On other hand, homophone LS can reduce the probability difference between right and wrong homophones, such that LM can correct the wrong path selection in decoding.

5.4. Extension of homophone smoothing by fuzzy pronunciation

Equation (16) can be further improved by fuzzy pronunciation via Chinese Pinyin as follows:

\[
\text{HOMO}_n(y_{u,k}) = \begin{cases} 
0.6, & \text{if } k = k_0, \\
0.15, & \text{if } k \in \text{Homo}(k_0), \\
0.15 + \frac{0.1}{M}, & \text{if } k \in \text{Simi}(k_0), \\
0.15 + \frac{0.1}{M + 1}, & \text{Others},
\end{cases}
\]

in which \( \text{Simi}(k_0) \) is the set of indexes of elements of \( \text{Simi}(c_u) \) in \( \{1, \ldots, K\} \) and \( M \) is the size of \( \text{Simi}(k_0) \). \( \text{Simi}(c_u) \) contains all characters that have fuzzy pronunciation with \( c_u \). Formally, it can be defined as following

\[
\text{Simi}(c_u) = \{ c | c \text{ shares fuzzy pronunciation with } c_u \}.
\]

The character \( c \) shares fuzzy pronunciation with \( c_u \), means that either \( c \) and \( c_u \) share similar consonant (e.g. ‘z’ and ‘zh’) or similar compound vowel (e.g. ‘in’ and ‘ing’).

6. References

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